Global Positioning System (GPS) Bias Correction and Habitat Analysis of Mountain Goats *Oreamnos americanus* in the Cascades of Washington State, USA

by

Adam G. Wells

Accepted in Partial Completion
of the Requirements for the Degree
Masters of Science

Moheb A. Ghali, Dean of the Graduate School

Chair, Dr. David O. Wallin

Dr. Clifford G. Rice

Dr. Michael J. Medler

MASTER'S THESIS

In presenting this thesis in partial fulfillment of the requirements for a master's degree at Western Washington University, I agree that the Library shall make its copies freely available for inspection. I further agree that copying of this thesis in whole or in part is allowable only for scholarly purposes. It is understood, however, that any copying or publication of this thesis for commercial purposes, or for financial gain, shall not be allowed without my written permission.

Signature ______________________________

Date ______________________________

Global Positioning System (GPS) Bias Correction and Habitat Analysis of Mountain Goats *Oreamnos americanus* in the Cascades of Washington State, USA

A Thesis
Presented to
The Faculty of
Western Washington University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science

by

Adam G. Wells

July, 17th 2006

Abstract

Variation in habitat selection by the mountain goat is not well understood due to the difficulties of monitoring animal movement in all months of the year. The use of GPS wildlife telemetry collars offered an opportunity to overcome this obstacle, however satellite acquisition problems associated with global positioning system (GPS) wildlife telemetry collars create an observational bias of animal locations towards areas of favorable signal reception. To correct for this bias in data from GPS collared mountain goats *Oreamnos americanus* in the Cascades of Washington State I used an intensive field sampling exercise to calculate the amount of variation in position acquisition rates (PAR) explainable based on remotely sensed vegetation and topographic landscape characteristics in a geographic information system (GIS) framework. To statistically model the predicted GPS position acquisition rate across the entire the mountain range, I used non-linear mixed modeling with Akaike's Information Criteria (AIC) and a generalized estimating equation (GEE), autoregressive correlation structure (m =1), to account for the random effects of the binary clustered experimental design. I used vegetation data from satellite imagery provided by the Interagency Vegetation Management Project (IVMP) and a 10 m digital elevation model (DEM) as predictor variables. I sampled GPS PAR at 543 sites across two study areas, the western and eastern cascades, which cover roughly 5 million hectares. I analyzed the data at two spatial scales, 25 m^2 and 625 m^2. I developed the final model at the 25 m^2 resolution using a single square extraction window and had an area under the receiver-operating curve (ROC) of 0.70 and 0.69, respectively. Both models fit with expected ecological patterns. These two models were combined into one GIS raster file that predicted GPS PAR across the entire mountain range. These data used with an inverse weighting scheme reduced the signal reception bias found in a habitat study of GPS collared mountain goats. The correction factor helped to account for habitats likely used by coastal ecotype mountain goats but unfavorable to satellite acquisition. These understandably widely overlooked habitats, lower elevation forests with dense canopy cover, may provide over-wintering sites for mountain goats. I analyzed data collected over two years worth of tracking 39 GPS collared mountain goats, over 86,000 locations, in the Washington Cascades. Each location was weighted with inverse of the predicted GPS PAR to account for the GPS bias. I used a weighted logistic regression procedure with Akaike's Information Criteria (AIC) to choose the most parsimonious model out of an *a priori* selected set of models. Predictor variables were derived from vegetation layers developed by the Interagency Vegetation Mapping Project (IVMP) and a 10 m digital elevation models (DEM). Candidate models were developed on the basis of ecological relevance and available GIS data. I partitioned the data into eight datasets, based upon elevation quartiles of mountain goat locations and a northern and southern division of available sites. The individual habitat maps were mosaiced into one map and compared with a map generated with the same models not taking into account the weighting factor. The weighted models classified more terrain as habitat and had slightly higher classification accuracies. The final product will assist with management activities, conservation planning and ecological studies of Washington's endemic mountain goat populations.

Acknowledgements

This work was part of a cooperative research project on the mountain goat *Oreamnos americanus* in conjunction with Sauk-Suiattle Indian Tribe (SSIT), the Washington Department of Fisheries and Wildlife (WDFW), Western Washington University (WWU), the U.S. Forest Service and the U.S. National Park Service. This work was possible thanks to the hard work of Dr. David O. Wallin (WWU), Dr. Clifford G. Rice (WDFW), Doug McMurtrie (SSIT), Chris Danilson (SSIT) and Wan-Ying Chang (WDFW). SSIT, WDFW, Seattle City Light, U.S. Environmental Protection Agency, U.S. Forest Service, U.S. National Park Service and the U.S. Fish and Wildlife Service provided funding to complete this work. Recognition is due to Colin Shanly, Amber Potter, Adrian Laine, Andrew Test, Mackenzie Malloch, Kimberly Morris, Kelsey Adkisson (for artwork), Wyatt Griffiths, Frazier Coe, Patricia Bilskis and Brett Shattuck for hauling lead batteries all over the Cascades.

Table of Contents

List of Figures

List of Tables

Chapter One:

WILDLIFE TELEMETRY GLOBAL POSITIONING SYSTEM (GPS) BIAS CORRECTION IN THE CASCADE MOUNTAINS OF WASHINGTON STATE, USA

Introduction

The addition of Global Positioning System (GPS) receivers to wildlife radio telemetry collars has enabled automated position locating and data recording that has largely overcame seasonal, daily and weather related observational biases reflected in traditional wildlife telemetry studies. Automated data collection reduced the stress and biases associated with repeated disturbance of study animals and decreased positional errors of animal locations. Refinements in hardware, software and the deactivation of selective availability has reduce positional error to 10 m or less under optimal conditions (Johnson & Barton 2004). This level of accuracy generally exceeds the spatial resolution of satellite imagery and Geographic Information Systems (GIS) data layers used to model habitat. (Rempel & Rodgers 1997; Rodges 2001; Di Orio *et al.* 2003).

Despite these advantages, GPS receivers often fail to obtain a position under dense forest canopy or when topography blocks signals from orbiting satellites (Gerlach & Jasumbach 1989). Ignoring this issue, when evaluating data from GPS-collared animals, provides a biased view of habitat use towards areas of favorable GPS reception (Rempel *et al.* 1995; Deckert & Bolstad 1996; Edenius 1997; Dussault *et al.* 1999; Gamo & Rumble 2000; Licoppe 2001; Rodgers 2001; D'Eon *et al.* 2002; Taylor 2002; Di Orio *et al.* 2003; Frair *et al.* 2004; Cain *et al.* 2005; Sager 2005). In light of these findings, I addressed the GPS Position Acquisition Rate (PAR) across the Cascade Mountain range of Washington State for incorporation into a habitat analysis of GPS collared mountain goats *Oreamnos americanus*.

The Cascade Mountains of Washington State represent a sizeable portion of the historic range of the mountain goat (Johnson 1983). Mountain goats inhabited the Pacific Northwest of the United States and coastal British Columbia Canada for at least the past 12,000 years (Nagorsen & Keddie 2000). This highly recognized, uniquely adapted ungulate has also been literally interwoven into the cultural histories of the indigenous people of the region. Since European settlement, this charismatic species experienced a substantial population decrease in many parts of their native range (Table 1). In particular, this decline has been readily apparent in the traditional tribal territories of the Sauk-Suiattle Nation, located in the vicinity of Darrington, WA with decreases of 70-90 over the last 40 years (Ryals, pers. com.)

Between 2003 and 2005, the Washington Department of Fish and Wildlife (WDFW) captured and collared 50 mountain goats in the Washington Cascades to establish a baseline study of mountain goat ecology. They hoped to assess the magnitude, extent and causes for declines in Washington's endemic mountain goat populations. As part of this study, to offset the aforementioned GPS bias, I have evaluated the relative influence of topography and vegetation on GPS PAR with a field-sampling regime. I hypothesized that the rates at which GPS collars successfully record data were predictable based on remotely sensed vegetation and GIS derived topographic characteristics. In Chapter one, I developed a predictive model encompassing the whole of the Washington Cascade mountain range to weight location data acquired from GPS-collared animals during a habitat analysis. The final products were designed to assist in future wildlife management efforts, conservation activities and habitat connectivity analysis taking into account the observational bias generated by GPS wildlife telemetry collars towards areas of favorable satellite signal reception.

Review of Previously Published GPS Bias-Correction Studies

The GPS collar bias issue has stimulated interest in the development of new methodologies to minimize these observational biases. The typical methodology involves placing collars in the field, programmed to record waypoints at a consistent interval for a minimum of 24 hours. The orbital geometry of the constellation of GPS satellites repeats once per sidereal day, about 23 hours and 56 minutes (Hoffmann-Wellenhof *et al.* 1997), so a 24-hour sampling interval covers the full range of satellite geometries at a given site. At each sample location, data from the collars yields GPS PAR, or the percentage of successful fix attempts. Site characteristics either observed on the ground or derived from GIS layers provide predictor variable. A statistical model built upon these data predicted GPS PAR based on the observed site conditions or across the entire landscape with a GIS.

Since 1995, several published studies utilized this basic approach (Table 2). These studies evaluated GPS performance across areas of a few tens of thousands of hectares. Many took place in Canada including studies in coastal and interior British Columbia (Taylor 2002; D'Eon *et al.* 2002), Alberta (Frair *et al.* 2004), Ontario (Rempel *et al.* 1995) and Québec (Dussault *et al.* 1999). Studies in the United States occurred in California (Di'Orio *et al.* 2003) the Black Hills of North Dakota (Gamo & Rumble 2000) and in the temperate forests of the Olympic Mountains of Washington State (Sager 2005). The progression of the these studies reflect an increased understanding and shift of focus from initially addressing the GPS PAR observational bias issues, to quantifying the effects of the bias and finally correcting for it. For a more complete list of published studies see Cain *et al.* 2005.

Methods

Study Area

The study area spanned the indigenous range of the mountain goat in the Cascades of Washington State (Johnson 1983) divided along the cascade crest into two regions; east (2,585,240 hectares) and west (2,744,521 hectares) (Fig. 1). The major ecological zones occupied by mountain goats included the subalpine and alpine communities and to a lesser, fairly unknown, extent the montane. The Cascades house five stratovolcanoes, four of them over 3200 m, and numerous peaks surpassing 2000 m. The combination of dense forests and narrow valleys at lower elevations and treeless ridgelines higher up provided a range of conditions for testing GPS receivers. The spatial extent of the Inter-Agency Vegetation Mapping Project's Western and Eastern Cascades of Washington (O'Neil *et al*. 2002) defines the study area boundaries and provided the available remotely sensed vegetation data.

The montane zone generally occurred between 450 m and 1050 m extending from the dense, lower elevation forests up to the beginnings of the subalpine zones. In the western and northern Cascades, the Pacific Silver fir/ Western hemlock *Abies amabilis/Tsuga heterophylla* forests represent the most common forest community (Franklin & Dryness 1988). Common associated overstory species include: Douglas-fir *Psuedotsuga menziesii* (Mirb. Franco), Red alder *Alnus rubra* (Bong.) and Western red cedar *Thuja plicata* (Donn ex D. Donn). The eastern slope of the Cascades have more drought tolerant and fire resistant tree species; ponderosa pine *Pinus ponderosa* (Dougl. ex Laws) dominate the landscape at lower elevations. Common associates include Douglas-fir, Engelman spruce *Picea engelmannii* (Parry ex Engelm.), Subalpine fir *Abies lasiocarpa* (Hook. Nutt.) Western larch *Laryix occidentallis* (Nutt.) and Lodgepole pine *Pinus contorta* (Dougl. Ex Loud.).

In mesic montane sites, these trees often occurr with Skunk-cabbage *Lysichitum ameicanum*, Ladyfern *Athytium fillix-femina*, Devils club *Oplopanex horridum* and Swordfern *Polystichum munitum*. At slightly drier sites, common associates include huckleberry *Vaccimuim alaskaense*, dogwood bunchberry *Cornus canadensis*, Salal *Gaultheria shallon*, Vanilla leaf *Achlys triphylla* and Oregon Grape *Berberis nervosa* (Topik

1986). At some very dry sites, especially further south in the range, madrone *Arbutus menziesii* and Ocean Spray *Holodiscus discolor* occur (Topik 1986). At higher elevations *Xerophyllum tenax*, Cascade azalea *Rhododendron albiflorum* and Fool's huckleberry *Menziesia ferrugie*a commonly grow (Brockway 1983).

The subalpine zone ranged between 1050 m and 1500 m and consisted of a mixture of forests and meadows extending up to tree line. The lower regions of the subalpine zone transition from western hemlock to mountain hemlock *Tsuga mertensiana* (Bong. Carr.) with tree stature often reaching full development. Pacific silver fir grows across both the upper montane and into the subalpine zones. At some of the higher elevations, subalpine fir and alaska-cedar *Chamaecyparis nootkatensis* (D. Don, Spach) exist. Krummholz and dwarf shrub communities commonly develop at the higher elevations due to the effects of wind, snow and temperature (Taylor 1986).

The most pronounced subalpine meadows develop beneath the upper portions of tree line in avalanche paths (Taylor 1986) and after forest fires (Johnson 1983). Vegetation community types found within the subalpine include: snowbed (Saxifrage-Woodrush *Saxifraga tomliei-Luzula piperi* and Sedge *Carex nigricans*) mesic herb (Lupine *Lupinus latifolis*, Fescue *Festuca viridula*, Huckleberry *Vaccinium deliciosum*, sedge *Carex spectabilis*, Buckwheat *Polygonum bistortoides*, Valerian *Valeriana sitchensis* and Daisy Fleabane *Erigeron pereginus* var. *scaposus*) dwarf shrub (Heather *Cassiope mertensiana*, Mountain-Heath *Phyllodoce empetriformis* & *P. glanuliflora*, Crowberry *Empetrum nigrum*, Bearberry *Arctostaphylos uva-ursi*, Partridgefoot *Luteka pectinata*, Huckleberry *Vaccinium deliciosum*, Everlasting; Pusstoes *Antennaria lanata*, willow *Salix nivalis* & *S. cacadensis* and Mountain-avens *Dryas octopetala*) and dry gaminoid (Oatgrass *Danthonia intermedia* and Sedge *Carex spectabilis*, *C.* var. *pseudoscicrpoidea)* (Douglas & Bliss 1977).

The alpine zone, dominated by rock and ice and free of overstory vegetation, extended up from subalpine zone around 1500 m to the mountain summits. The high alpine tundra provides areas for evaluating GPS-collar performance under the optimal conditions of no canopy and views of the sky that are unobstructed by topography (Rempel *et al.* 1995). The alpine and subalpine zones also typify common impressions and interpretations of mountain goat habitat.

Herbfields, fellfields, and boulder fields characterize this zone (Taylor 1986). Vegetation community types found within these features included: dwarf shrub (Mountain-Heath *Phyllodoce grandiflora* & *P. empetriformis* and Heather *Cassiope mertensiana*), mesic herb (Lupine *Lupinus latifolis* and Fescue grass *Festuca viridula*), dry gaminoid (Oatgrass *Danthonia intermedia*, Reedgrass *Calamgrostis purpurascens*, Sedge *Carex spectabilis*, *C. phaeocephala*, *C. scirpoidea* var. *pseudoscicrpoidea* & *C. nardina*, and Kobresia *Kobresia myosuroides*) and snowbed communities (Sedge *Carex breweri C. capitata* & *C. scirpoide*, Cinquefoil *Potentilla diversifolia* var. *diversifolia*, Goldenrod *Solildago multiradiata*, Willow *Salix cascadensis* and Fescue *Festuca ovina*) (Douglas & Bliss 1977).

Field Work

I tested collars throughout the study area during the summer of 2004, winter 2004-2005 and summer 2005. Prior to collection of field data, I benchmarked the Vectronic-Aerospace GPS Plus collars (v6, Vectronic Aerospace, Berlin Germany) at a known location with an unobstructed view of the sky to ensure proper functioning (Moen *et al.* 1997). For logistical reasons, I sampled sites near existing trail networks. Random selection of field sites for collecting PAR data was not practical due to the rugged inaccessible terrain. I sampled above the minimum expected elevation of a mountain goat, generally 1000 m, and placed collars at least 200 m apart. Field placement of GPS units mimicked the height and orientation of a GPS unit on a collared mountain goat, approximately 1.0 m above ground. GPS units were secured with bamboo tripods or natural materials found on site, including saplings, tree branches, downed logs, stumps located and rocks. Field measurement taken at each site for ground-truthing GIS variables included: aspect, slope, elevation and canopy cover. Site selection focused on areas with relatively uniform vegetation characteristics within 30-50 m of the GPS units. Ignoring this issue, and using sites near the edge of a forest or alpine meadow, for example, could have created small miss-registration of the GIS raster files resulting in differences between actual site conditions and the GIS data.

GPS units were programmed to attempt a 3-minute fix every 30 minutes for no less than 24 hours (Frair *et al.* 2004). Positional dilution of precision (PDOP) of the Vectronic-Aerospace collars reached 48.6 when a fix attempt failed. The collars ignored satellites within 5° of the horizon in order to minimize multi-path errors (Schulte, personal communication). I calculated average positional location for all successful fixes for data extraction and calculated PAR as the percentage of successful fix attempts (2D and 3D fixes) during the full duration of GPS unit deployment (D'Eon *et al.* 2002).

I also deployed a Trimble GeoExplorer3 handheld GPS unit (v1.20, Trimble Navigation Ltd., Sunnyvale, California USA) within 3 m of the collar at some of the sites to test relative GPS PAR between brands and to determine if GPS PAR model development was possible with alternative manufacturers once collars were unavailable. Configuring the Trimble units with custom external battery packs enabled 24-hour continuous operation. I programmed a 15-minute interval of fix attempts to match the 30-minute interval of the Vectronic collars. I set the Trimble horizontal dilution of precision (HDOP) mask to 60 initially, the signal to noise ratio mask to 1 and an elevation mask of 5°. I reset the HDOP to 48.6 after preliminary data collection to match the Vectronic units. After analyzing the performance of Vectronic versus Trimble data from the summer of 2004, I analyzed the relative performance of Vectronic units. During the winter of 2004-2005, I tested the Vectronic collars against each other to look at simultaneous performance of the collars under equivalent site conditions. At a limited number of sites I placed two collars within 1 m of each other programmed to record fixes on the same 30-minute interval.

GIS Data

Vegetation Predictor Variables:

Variables derived for statistical modeling of GPS PAR came from existing, 25 m resolution, raster files created by the Interagency Vegetation Mapping Project (IVMP), utilizing Landsat imagery from the mid-1990's (O'Neil *et al.* 2002; Browning *et al.* 2003). The IVMP data consists of four vegetation layers: percent total vegetation cover (TVC), percent conifer cover (CC), percent broadleaf cover (BC) and quadratic mean diameter of overstory trees (QMD). Each of these four layers the IVMP provids as continuous variables, but recommends subdividing each layer into three or four user-defined categories based on tradeoffs between accuracy and category size. To remain consistent with the release documentation of the IVMP data sets and accuracy assessment, I classified each vegetation layer into discrete categories based on the frequency distribution of the number of sites in each class (Table 3). I attempted to maintain an even balance of the number of sites in each class. Documentation provided by IVMP indicates this categorization of data layers with classification accuracies of approximately 78% (TVC), 73% (CC), 46% (BC) and 62%

(QMD) for the westside and 68% (TVC), 55% (CC), 61% (BC) and 57% (QMD) for the eastside.

Topographic Predictor Variables:

I derived topographic predictor variables from a 10 m digital elevation model (DEM). I masked the necessary DEM to the spatial extent of the IVMP data and resampled the pixel size to 25 m. In addition to elevation, I created slope, aspect and sky visibility (Deckert & Bolstad 1996; Gamo & Rumble 2000; D'Eon *et al.* 2002) data layers. The sky visibility layer considered the uneven distribution of GPS satellite orbits in the sky. The existing constellation of GPS satellites, distributed in 6 orbital planes inclined at 55° relative to the equator (Hoffmann-Wellenhof *et al*. 1997), dictates that no GPS satellites pass over a substantial portion of the northern portion of the sky. In generation of the sky visibility layer, I excluded portions of the sky within this "hole" from the calculations and expected samples located on northerly aspects to achieve lower PAR then those on southerly ones (Appendix A).

Stratification

The logistical challenges associated with sampling the full range of conditions across a 5 million hectare study area warranted substantial consideration. Examination of the IVMP and DEM files insured field-sampling efforts focused on the major combinations of GIS derivable topographic and vegetation site characteristics in the region. I stratified both study areas using a merged set of predictor variables (Table 4) namely forest type (based on first three IVMP layers), QMD classes, slope combined with aspect (flat, steep and north facing, or steep and south facing) and sky visibility. I used identical stratification rules for both areas with the exception of QMD classification. Cross-tabulation resulted in 81 different combinations of these four variables in the western half of the study area and 54 in the eastern half. Due to logistical constraints, the majority of field sampling on the western slope concentrated in the northern portion (Mount Baker-Snoqualmie National Forest.) of the study area and on the eastern slope in the southern portion (Wenatchee National Forest).

Data Analysis

Extraction:

For each sample site, I extracted predictor variables from the IVMP and DEM layers. I developed two sets of predictor variables for each half of the Cascades (Table 5). The first sets of variables were extracted for the single 25 m by 25 m grid cell that contained the sample site. The second set of predictor variables were extracted for a three by three or 9 cell (75 m by 75 m) window that centered on each sample site. These two data sets enabled examination of the relationship between GPS performance and site conditions at two spatial scales.

Modeling:

I initially examined the breadth of coverage that field sampling efforts yielded based upon the study area stratification for both. I looked at relative performance of GPS units between brands and among collars and screened for outliers based on cluster size and improbable GPSPAR ranges.

I used non-linear mixed modeling logistic regression, information theory and generalized estimating equations (GEE) to model GPS PAR as clustered binary responses (Pendergast *et al.* 1996; Heagerty 1999; Horton & Lipsitz 1999; Hosmer & Lemeshow 2000; Teachman & Crowder 2002). Fix attempts at each trial site, coded as successful or not, had the same predictor variables over the course of the entire sampling period. The lack of independence due to repeated observations at each sample site required modeling of the internal correlation structure by means of a GEE. The GEE modeling changed the values of the standard errors bounding the parameter coefficient estimates from those obtained by ordinary logistic regression. Use of the auto-regressive (m=1) GEE was based on the notion that the correlation structure of the waypoints clustered by site had some diagonal relationships. The fact that the constellation of the GPS satellites repeats just short of a full 24 hour day meant that the correlation structure within sites shifted as a function of position within the cluster.

For each of the two spatial resolutions, I *a priori*-selected a series of models for testing (Burnham & Anderson 2002). I tested a global model utilizing all of the applicable predictor variables and selected model subsets. I selected the most parsimonious models based on non-linear mixed modeling procedure (Appendix B) and the AICc for each extraction window. I calculated the area under the receiver-operating curve (ROC) for both spatial scales' most parsimonious model using the ROC package in R (Gentleman *et al.* 2004). The parameter estimates, confidence intervals and robust standard error estimates were generated with SAS (8.0, SAS Institute Inc. Cary, NC) using an auto-regressive GEE. I used the resolution in the applied models that optimized their ROC scores (Pearce 2000) and calculated variance inflation factors (ĉ) for both provinces.

I analyzed site level GPS PAR data based on the most parsimonious models for the optimal extraction window. I randomly split the data in half and regenerated parameter estimates with the selected models using a model building subset and calculated GPS PAR for the remaining model testing data. I applied the model testing data created from all acquisition attempts to the site level data of each GPS PAR test site and plotted observed GPS success against the predicted GPS PAR of each trial site. I calculated the coefficient of determination to quantify the amount of variation explained by the models (Menard 2000)

I painted predictive maps of GPS PAR for each province and finally merged them into one complete data layer. I used ArcMap 9.0's Spatial Analyst Raster calculator in order to calculate the pixel-by-pixel values of predicted GPS PAR across both study areas. I mosaiced the two study areas together to form one layer for the entire Cascade Range of Washington State. I designed the final data layer to incorporate into a habitat analysis based upon an inverse weighting scheme of predicted GPS PAR for a fix acquired from collared animals. These final data layers calculated the predicted GPS PAR for each 25 X 25 m pixel based on the logit formula (eqn 1) and the predicted probability (eqn 2).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_3 + \ldots + \beta_p X_p + e \qquad \text{eqn 1}$$

$$\text{GPS PAR} = \text{Exp}Y/(1+\text{Exp}Y). \qquad \text{eqn 2}$$

Results

Ground Truthing

A correlation analysis showed a high degree of correlation between field measurements of topographic features and GIS predictor variables. Elevation measured in feet in the field and the data from the 10 m DEM had a simple correlation coefficient of R = 0.92. Aspect and slope, both derived from the 10 m DEM had values of R = 0.56 and R = 0.60, respectively. Vegetation data recorded in the field with a spherical densiometer and total vegetation cover derived from the IVMP as a continuous variable had a lower value of R = 0.37 (Zar, 1996).

Stratification

During the summer of 2004, I sampled GPS PAR at 209 sites in the western Cascades, 64 sites in the winter of 2004-2005 and 51 more in the summer of 2005 for a total of 324. During the summer of 2005, I sample 219 sites on the eastern side of the cascades for a grand total of 543 sites across the entire Washington Cascades.

Of the 81 possible combinations of variables (Table 4) in the west side stratification model, 42 conditions each individually covered more than 0.5% of the study area for a total of 94.33% of the western cascade province. I sampled 39 of these 42 combinations. The three combinations omitted, defined as Mixed/Broadleaf forests with varying topography, covered 2.59% of the study area. All together, west side sampling efforts covered 91.74% of the defined stratification classes by area.

Of the possible 54 combinations of variables on the east side, 34 each individually covered more than 1% of the study area, for a total of 88.9% of eastern cascade province. I sampled 33 of these 34 stratifications for a grand total of 94.2% of total area. One dominating cover type (flat open sites with high sky visibility) accounted for 21.6% of the total area, and 16.4% of the samples.

By elevation, the distribution of our sample sites was similar to that of over 30,000 mountain goat locations (from over 40 mountain goats). I over-sampled slightly at lower elevation (<1,000 m) and under-sampled slightly at higher elevations (>1,600 m).

Collar comparison

Trimble vs. Vectronic:

Of the 138 sites with both a Trimble GeoExplorer3 data logger and a GPS collar the correlation coefficient (Zar 1996) of GPS PAR between these units was $R = 0.67$ (Fig. 2). Most of the results of GPS PAR fell within the 90-100% range.

Vectronic vs. Vectronic:

Of the 16 sites during the winter of 2004-2005, I placed two Vectronic collars under "identical" conditions to assess relative GPS PAR. The correlation coefficient (Zar 1996) of GPS PAR between these sites was $R = 0.83$ (Fig. 3).

Global positioning system position acquisition rate; GPS PAR

Vectronic Collars:

The 324 western cascade sample sites originally consisted of 20,740 acquisition attempts. I removed seven sample sites entirely due to poor GPS PAR and only used a maximum of 48 attempts per sample site for computational reasons. This reduced the data set to 15,550 acquisition attempts. I retained all the 219 eastern cascade sample sites tallying 11,057 acquisition attempts since the data had a smaller range of sample site fix attempts. The more even sampling allowed for successful modeling of the correlation structure. Large differences in the number of fix attempts per cluster caused statistical program failure. The average overall success rate in the western study area was 78.8% and 92.4% in the east.

Out the entire set of *a priori* selected models, the three highest ranked models in each data set had Akaike's weights >0.1 (Table 6). The most parsimonious western cascade model had an area under the ROC of 0.70 based on a one cell window and 0.69 based on a nine cell extraction window. This indicated a slightly better ability of the one cell western cascade model to correctly differentiate between predicted GPS success and observed success then the nine cell extraction window. The western cascade nine cell extraction window also had small effect size (<.001) for two variables and multiple confidence intervals bounding zero. The eastern cascade models had nearly equivalent areas under the ROC (0.68) based on a one cell window and a nine cell window. Considering that both spatial resolutions returned the same model parameters for the most parsimonious eastern province models this result was not unexpected. I opted to use the western cascade model based on a one cell extraction window due to the area under the ROC and for consistency sake, the same spatial resolution on the east side.

The coefficients for the one cell extraction windows for Cascade GPS PAR (Table 7 & 8) indicated strong suggestions of significance and confidence intervals that did not bound zero. These models also have similar variable types, the cosine of aspect in radians and one entire class of categorical vegetation variables. The global models' yielded variance inflation factors for the western province ($\hat{c}$ = 8.4) and eastern province ($\hat{c}$ = 19.5) indicating some structural lack of fit.

Analysis of the coefficient of determination based on randomly splitting the data and regenerating parameter estimates based upon the previously selected model returned similar values for both provinces. The western cascades model ($R^2 = 0.175$) and the eastern ($R^2 = 0.184$) explained almost 20% of the variation of GPSPAR based on remotely sensed vegetation and topographic predictor variables (Fig. 4 & Fig. 5).

Mountain goats:

I looked at approximately 10,000 GPS waypoints over the course of two years of summer and winter data from goats in the Mt. Baker-Snoqualmie National Forest. I arbitrarily defined summer and winter seasons by dates; as July 1st to August 15th and November 15th to January 1st, respectively. Summer GPS PAR rates from collared goats exceed 50% for each animal with the majority of rates above 80% ($\bar{x} = 81\%$). Conversely, as expected, most winter GPS PAR rates decreased and were generally around 40% ($\bar{x} = 44\%$) (Fig. 6).

Painted PAR map

To include estimated GPS PAR (Fig. 1) into a habitat analysis across the entire study area, I created a data layer based on the selected model based on the one cell extraction window (Table 7 & 8). The western cascade model included the cosine of aspect in radians and the amount of coniferous coverage while the eastern cascade model included the cosine of aspect in radians and the amount of total vegetation cover. As expected, the cascades generally showed a much greater probability GPS PAR east of the pacific crest. Surprisingly, southerly aspects show a lower probability of success throughout the range. A closer examination of the odds-ratios of obtaining of GPS fix by aspect binned into the eight cardinal direction revealed this pattern in both data sets. The final model also only yielded a range of values from 64% to 99%.

Discussion

The predictive ability of the bias correction model developed based on the one cell extraction window for the Cascades of Washington performed as expected based on the range of values previously reported in the literature. This study however, encompassed a much larger area and therefore intensive sampling scheme and stratification. I over sampled lower elevations where expected bias in the mountain goat data prevailed. I omitted a few areas of low topographic relief and vegetative obstructions from the sampling. Collar comparison between brands dismissed future use of Trimble Geo3 Explorer's from inclusion in model development. Comparison among Vectronic units and predictive power suggested that micro-site features played a critical and hereby unexplained role in GPS PAR. The final chosen models for both sides of the cascades fit with ecological expectations and had expectable ROC scores but a measure of over dispersion entering the data. The final product, a GIS raster dataset, incorporated into habitat modeling as the inverse of expected GPS PAR reduced observational bias of GPS collared mountain goats.

Stratification

At 5 million hectares, this analysis covered a much larger area than previously published studies of GPS PAR both in terms of the number of sample sites and the spatial extent of the study area. I felt confident that the stratified sampling scheme provided adequate coverage in order to extend the results to the entire study area and range of conditions therein. On the west side, the combinations of vegetation and topography that I omitted represented mixed and broadleaf forest types that I did not expect to be used by mountain goats nor did I expect to be of any consequence to GPS PAR due to the predominately evergreen nature of the forest communities in western Washington. On the eastside, I did not sample stratification classes that composed 5.80% of the study area. Only one of these classes (southern facing open sites with sky visibility of 61-70%) composed more than 1% of the study area individually. Without empirical evidence, I expected a high GPS PAR at such sites with this classification.

The elevation distribution of sample sites resembled the distribution of available locations obtained from GPS-collared mountain goats. I slightly over-sampled lower elevations since these elevations typically had lower PAR due to denser forest cover and greater topographic obstructions. I anticipated that these sites presented greater challenges for adequately characterizing habitat use due to lower PAR. The elevation distribution of bias correction sample sites accounted for this expected range of data loss.

GPS data loss, and subsequent observational bias, from collared goats occurred more often in the winter when mountain goats descend to lower elevations (Fig. 6). Data acquired over two years of collection from collared animals thus exhibited the anticipated GPS bias that PAR-modeling efforts reduced. I felt justified applying the final GPS PAR model to the entire study area due to careful stratification of sampling across the full range of conditions occurring in the Cascades of Washington in accordance with the IVMP release documentation (O'Neil 2002 *et al.*; Browning *et al.* 2003) and available GIS topographic data.

Collar Comparison

In the side-by-side comparison of GPS units between brands neither the Trimble Geo3Explorer nor the Vectronic-Aerospace unit consistently outperformed the other. The low correlation between brands (Fig. 2) and the slightly higher correlation among Vectronic-Aerospace collars (Fig. 3) contradicted my expectations. These poorly correlated results suggested a performance difference between brands or possibly variation in performance among individual GPS units of one or both brands. I did not expect nor test for this possibility and found these results warranted dismissal of a bias correction model including any GeoExplorer3's data.

Given that these units were positioned a short distance apart (up to 3m), another possibility was that the differences in the position of tree boles and small canopy gaps relative to each unit may have been enough to block satellite signal access to a unit. The slightly higher correlation between the Vectronic units might be due to the use of identical units or it may simply have reflected the fact that these units were placed right next to each other rather than the maximum of 3 m apart. If this is indeed the case, then the correlation coefficient ($r = 0.67$) of the Trimble-Vectronic pairing provided a rough estimate of how much variability in PAR was explained on the basis of macro-scale site conditions derived from GIS data files.

Although the macro-scale conditions of vegetation and topography for both collars were identical, micro-site conditions, such as positioning of tree boles and canopy gaps, may have been quite different. The increased correlation coefficient among units placed closer together suggested the importance of fine scale features on GPS PAR. The remaining variation in PAR possibly controlled by micro-site conditions might be described on the basis of detailed stem maps and hemispherical photographs of the canopy. In principle, these measurements could be obtained for a limited number of sample points but unpractical to utilize over any study area of reasonable size. Another alternative might incorporate Light Image Detection and Ranging (LIDAR) data (Lefsky *et al.* 2002). LIDAR made it possible to quantify aspects of forest canopy structure including canopy height and vertical biomass distribution quickly and continuously over large areas. As LIDAR gains availability, incorporation of these data into GPS PAR analyses might facilitate characterization of micro-site features at a finer scale, both in terms of vegetation and topography.

Global positioning system position acquisition rate; GPS PAR

The final model developed for the Washington cascades predicted GPS PAR across mountain goat habitat and reduced observational bias generated by vegetative and topographic features of the landscape. Final predictor variables included: the total vegetation cover, coniferous coverage and aspect. The predictive model of GPS PAR developed from stationary collars sampled across the mountain range performed within the range of expectation based on previous research in this field. This supported the application of a bias correction factor to analysis of GPS data from collared mountain goats.

Once final models were selected for both extraction window sizes and for both study areas, I needed to select one or the other for final development. I opted to use the area under the ROC curve in order to distinguish if the one cell or the nine cells extraction window performed better. On the west side, the small difference between 0.69 (nine cell) and 0.70 (one cell) warranted use of the one cell model. The east side model areas under the ROC curves were virtually identical, so in order to remain consistent with the west side model I opted to use the one cell extraction window. Values >0.70 indicated "a reasonable discrimination ability appropriate for many uses," (Pearce & Ferrier 2000). The final model thus utilized one cell (25 m x 25 m) extraction window for the entire study area.

After selecting the models developed on the one cell extraction window, I tested the global models of both data sets for over dispersion and goodness of fit. Variance inflation values much greater then 4 indicated structure lack of fit and over dispersion of the data for both models (Burnham & Anderson 2002). The predictive model did not perform well at low predicted probabilities (<0.60) when compared with observed PAR rates, displaying poor model refinement (Fig. 4). The final data layer, however, had values ranging from 0.64 to 0.99.

These findings of predicted GPS PAR and low correlation among GPS units placed at the same site suggested an unmeasured component of the forest canopy heavily impacting GPS PAR. This, again, remained consistent with prior studies on this subject that explained only a portion of GPS PAR bias (Table 1). This GPS PAR bias correction study ultimately only reduced, but did not eliminate, bias due to satellite signal blockage. The scale that satellite signal interference occurred most likely surpasses the scale at which the predictive model operated. A broad characterization of the landscape, such as the 25 m resolution level, characterized those types of habitats where micro-site heterogeneity was likely to increase (i.e. increased canopy cover, larger trees and more conifers) but did not account for all site specific factors determining GPS PAR. Nevertheless, this model explained nearly one fifth of the variation in GPS PAR.

An alternative approach considered to correcting for GPS bias involved an iterative process to estimate missed animal locations based on predicted GPS PAR, known animal locations, and theoretical movements across the landscape (Frair *et al.* 2004). This approach however, warranted far more intensive data management, calculations and corrections for individually missed animal locations.

Mapping

The final data layers predicted GPS PAR for collared mountain goats across the western and eastern halves of the Washington Cascades. These combined into one final data layer predicting GPS PAR across both IVMP Washington Cascade regions. Much of these regions lie below 800m elevations beneath our minimum sampling efforts. The overriding nature of vegetation variables impacting GPS PAR more so than topography allow reasonable extrapolation of the model to these lower elevation. The analysis indicated that elevation alone was not a strong predictor of PAR. This suggested that the model performed adequately even at low elevations. Examination of the eastern reaches of the data layer where the mountains begin to merge with the central Washington highlands and deserts predicted a high PAR, as expected. Closer examination of detail on the map provided one counter intuitive finding. In the Washington Cascades, southern facing slopes predicted a lower GPS PAR, not what was expected based on the satellite sky plot

Applying such a model outside the study area and with different hardware was not recommended by any of the previous authors published in this field of research. I certainly agreed with the notion of not applying this model to areas outside the Cascades of Washington (although areas of the Oregon Cascades might have applied), however I considered the merits of applying this data layer to other GPS collared wildlife with in the region. The fundamental decision to do so lies within any future projects' objectives, resources available, known improvements or difference in hardware, margins of error and costs of a Type I or Type II error.

Tables

Table 1: Population estimates of mountain goats across portions of their native range since the 1960's depicting a long-term decline in the population.

British Columbia

- 1961-est. 100,000
- 1977-est. 63,000 (Macgregor 1977)
- 2000-est. 36,000-63,000 (Côté and Festa-Bianchet 2003)

Washington

- 1961-est. 10,655
- 1983-est. 7350 (Johnson 1983)
- 2005-est. 3500-4000 (Rice pers. comm. 2005)

Entire Range-introduced and native

- 2000-est. 75,000-110,000 (Côté and Festa-Bianchet 2003)

Table 2: Prior studies of GPS wildlife telemetry observational biases

Author	Test	Test Statistic	Independent Variable
• Rempel *et al.* 1995	[1]LR	X^2 ($P < 0.001$)	tree spacing
• Dussault *et al*. 1999	[2]SMLR	$R^2 = 0.16$ (fall)	tree height
		$R^2 = 0.34$ (winter)	tree height, basal area of deciduous trees
• Gamo & Rumble 2000	SMLR	$R^2 = 0.39$ (*P.ponderosa*)	slope, CC
		$R^2 = 0.40$ (*P.tremuloides*)	Visible Horizon, Dbh
		$R^2 = 0.50$ (*P.glauca*)	CC
• D 'Eon et al. 2002	SMLR	$R^2 = 0.22$	[4]CC, [5]SV
• Taylor 2002	SMLR	$R^2 = 0.76$	SV, [6]age, clearings
• Di'Orio et al. 2003	SMLR	$R^2 = 0.57$	basal area
• Frair *et al*. 2004	LR [3]AIC	ROC= 0.68	vegetation type, slope
• Sager 2005	LR	$\hat{c}$=1.0282	CC, SV, [7]elev., CC*SV

[1]LR= Logistic Regression, [2]SMLR= Stepwise Multiple Linear Regression, [3]AIC= Akaike information criterion, [4] CC=Canopy Cover, [5]SV=Sky Visibility, [6]age=Forest age & [7]elev.= elevation

Table 3: Discrete categorization of vegetative predictor variables for both the western (wcw) and eastern (ecw) cascades of Washington GPS PAR data with variables included in final models. Bold face type of the region indicates selected variables in final model.

1. Percent Total Vegetation Cover (TVC);
   - wcw & **ecw**: 0-60% , 60-90% & 90-100%
2. Percent Conifer Cover (CC);
   - **wcw** & ecw: 0-40%, 40-80% & 80-100%
3. Percent Broadleaf Cover (BC);
   - wcw & ecw: 0%, 0-10%, 10-20% & 20-100%,
4. Quadratic Mean Diameter of overstory trees (QMD);
   - wcw: 0, 0-25.4 cm, 25.4-50.8 cm & >50.8 cm
   - ecw: 0-12.4 cm & >12.4 cm

Table 4. Stratification variable organization and definition used in field sampling efforts of GPS PAR across the entire Cascades of Washington based on the IVMP data sets.

1. Forest type
   - Open: TVC <30%
   - Semi-open: 30% ≥ TVC < 70%
   - Conifer: TVC ≥ 70%; CC >= 70%
   - Mixed: TVC ≥ 70%; CC and BC < 70%
2. QMD

   Western Cascades
   - 0-30 cm
   - 31-60 cm
   - 61-190cm

   Eastern Cascades
   - 0-25cm
   - 25-190cm
3. Slope and aspect
   - slope < 20 degrees
   - north-facing slopes > 20 degrees
   - south-facing slopes > 20 degrees
4. Sky visibility
   - 0-60%
   - 60-70%
   - 70- 80%
   - 80-100%

Table 5. Definition of predictor variables and nomenclature thereof for a single cell and a nine cell sampling window used to build models for testing GPS PAR.

Type	Sampling Window	Variable	Nomenclature
Topographic	1&9	Cosine of radial aspect	ASP
	1&9	Slope (degrees); mean	SLP
	9	Slope; standard deviation	SLPSD
	1&9	Elevation (m); mean	ELEV
	9	Elevation; standard deviation	ELEVSD
	1&9	Sky visibility; mean	SV
	9	Sky visibility; standard deviation	
Vegetative	1&9	Mode of QMD[1]	QMD
	9	Number of QMD classes	
	1&9	Mode of BC[2]	BC
	9	Number of BC classes	
	1&9	Mode of CC[3]	CC
	9	Number of CC classes	
	1&9	Mode of TVC[4]	TVC
	9	Number of TVC classes	

QMD[1]=Quadratic mean diameter, BC[2]= Broadleaf cover, CC[3]= Conifer cover & TVC[4]=Total vegetation cove

Table 6. Results from model testing of Cascade GPS PAR based on a one and nine cell extraction window for the western and eastern Cascades of Washington State, USA shown with negative log likelihood (-LL), number of parameters (K), Akaike's information criteria (AICc), criterion difference (Δ_i) and weights (w_i).

Region	**Window**	**Rank**	**Model**	**-LL**	**K**	**AICc**	Δ_i	w_i
West	1	1	ASP& CC	5184.2	4	10378.5	0	0.81
		2	CC	5186.9	3	10381.8	3.3	0.16
		3	ASP, SLP, ELEV & TVC	5185.7	6	10385.3	6.8	0.03
West	9	1	ASP, SLP, ELEV, SV & TVC	6980.5	7	13972.5	0	0.40
		2	TVC	6983.2	4	13973.1	0.6	0.30
		3	ASP & TVC	6980.5	5	13973.1	0.6	0.30
East	1	1	ASP, TVC	2396.6	4	4803.2	0	0.63
		2	ASP, SLP, ELEV & TVC	2395.2	6	4804.4	1.2	0.35
		3	ASP, CC & QMD	2400.2	4	4810.4	7.2	0.02
East	9	1	ASP & TVC	2396.5	4	4803.0	0	0.46
		2	ASP, SLP, SLPSD, ELEVSD	2394.2	6	4803.3	0.3	0.40
		3	ASP, TVC, QMD & CC	2396.6	4	4805.3	2.3	0.14

Table 7. The most parsimonious selected model for the western cascades of Washington GPS position acquisition rate's parameters, coefficients *(β)* robust error estimates and confidence intervals at 323 (*n* =15,550; *m* =317).

Variable	*β*	Std. Err.	*z*	$P>\lvert z\rvert$	[*95%*]	
ASP	0.2568	0.1235	2.08	0.0376	0.0147	0.4989
CCdv2	-1.0156	0.3013	-3.37	0.0007	-1.6061	-0.4251
CCdv3	-1.7966	0.2799	-6.42	<0.0001	-2.3451	-1.2480
Intercept	2.6484	0.2584	10.25	<0.0001	2.1420	3.1549

Table 8. The most parsimonious model for the eastern cascades of Washington GPS position acquisition rate's parameters, coefficients (*β*) robust error and confidence intervals (*n* = 11,057; *m* = 219) based on a one cell extraction window (25 m) with an auto-regressive GEE (*m*=1) modeling correlation structure.

Variable	*β*	Std. Err.	*z*	$P>\lvert z\rvert$	[*95%*]	
ASP	0.4291	0.1685	2.55	0.0109	0.0989	0.7594
TVCdv2	-0.9634	0.3119	-3.09	0.0020	-1.5747	-0.3521
TVCdv3	-1.6989	0.2900	-5.86	<0.0001	-2.2673	-1.1306
Intercept	3.5887	0.2637	13.61	<0.0001	3.0719	4.1055

Figures

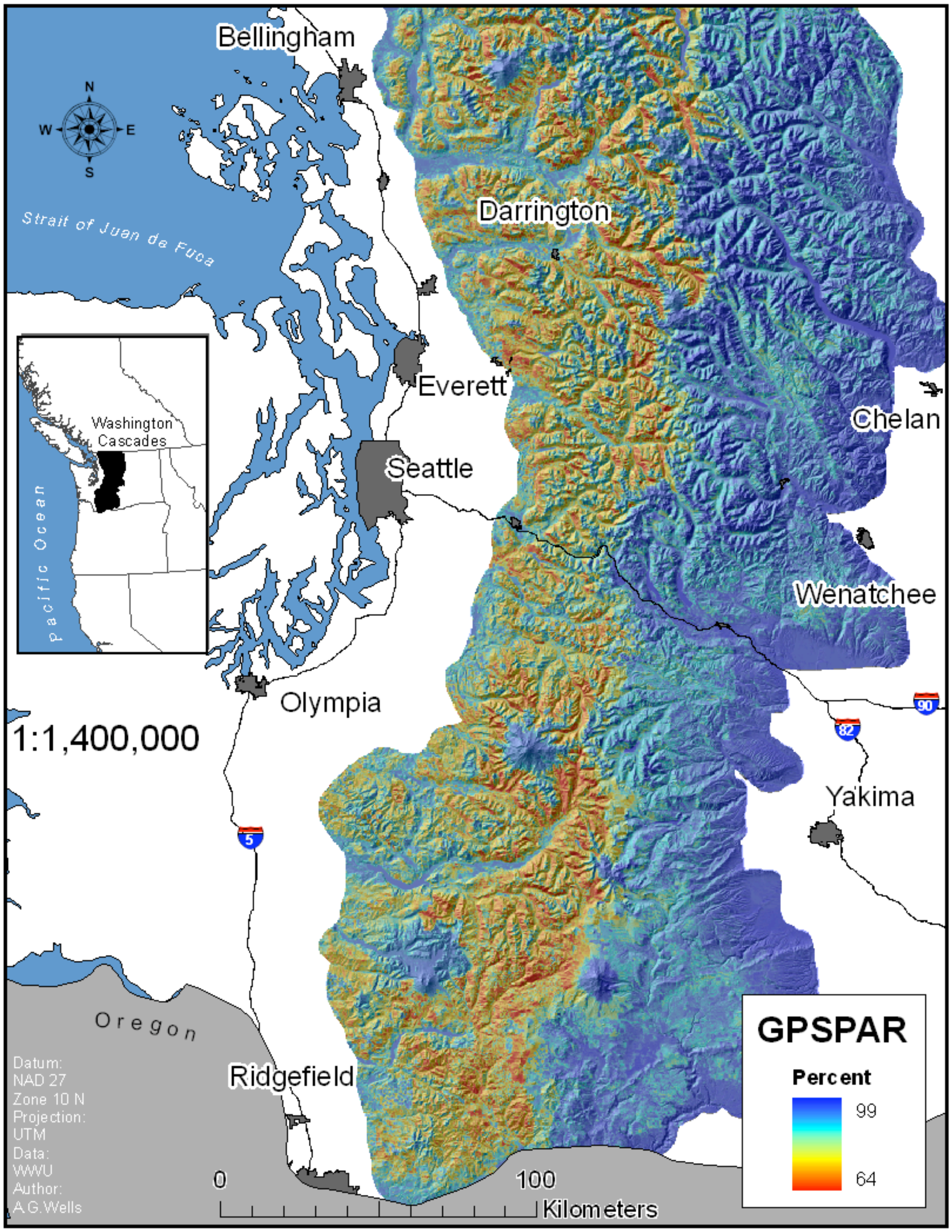

Fig. 1. Map showing predicted GPS Position Acquisition Rate (PAR) for the Cascades of Washington State used to offset bias generated during habitat analysis of GPS data from collared mountain goats. This combines the two study areas, east and west of the pacific crest, into a single unified data layer.

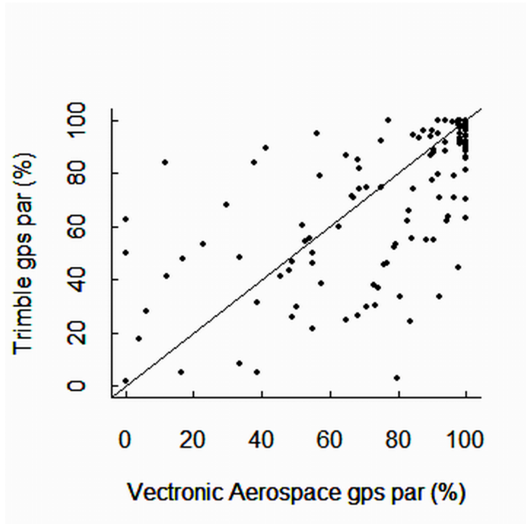

Fig. 2: Relative GPS PAR between a Trimble GeoExplorer3 and Vectronic-Aerospace wildlife telemetry collar at 138 sites across the Washington cascades shown with a one to one fit line.

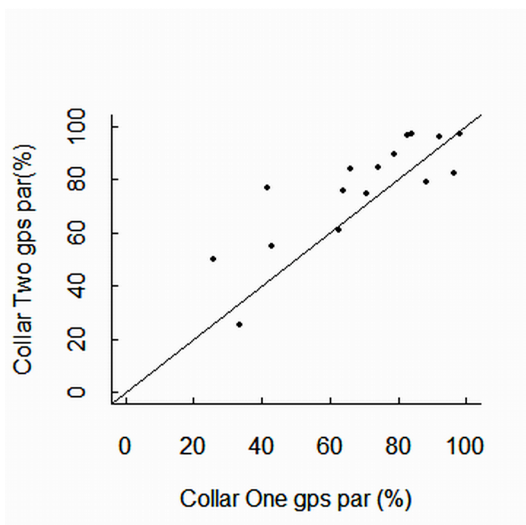

Fig. 3: Correlation of GPS PAR between two Vectronic-Aerospace GPS wildlife collars place within 1 m of each other at 16 different sites in the north cascades shown with a one to one fit line.

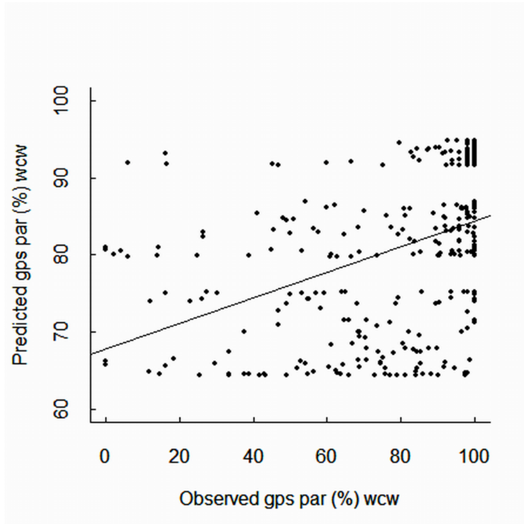

Fig. 4: A comparison of observed GPS PAR and predicted GPS PAR for the western cascades of Washington (wcw) based on a one cell extraction window using all fixes.

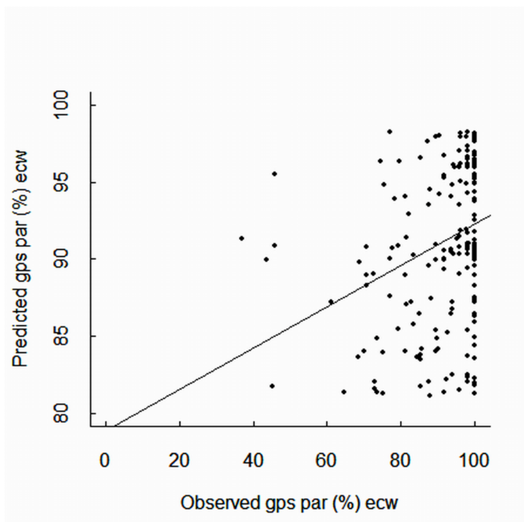

Fig. 5 A comparison of observed GPS PAR and predicted GPS PAR for the eastern cascades of Washington (ecw) based on a one cell extraction window.

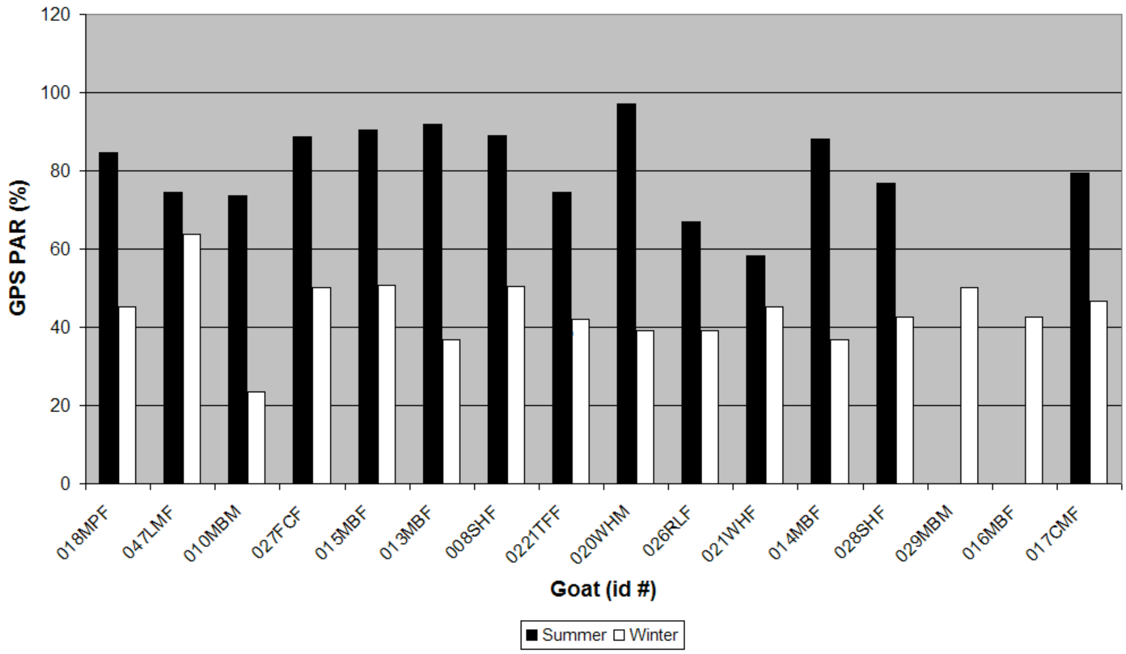

Fig. 6. Seasonal comparison of GPS PAR from collared goats in the northern region of the western cascades based on 10,000 locations obtained between July 15 to August 31 of 2004 and 2005 (black) and December 15 to January 31 during the winters of 2003-04 and 2004-05 (white).

Chapter Two:

HABITAT SELECTION BY MOUNTAIN GOATS *OREAMNOS AMERICANUS* IN THE WASHINGTON CASCADE

Introduction

Mountain goats inhabit some the most rugged terrestrial environments of the North American west (Côté and Festa-Bianchet 2003). The harsh environment that they inhabit results in low fecundity, low survivorship and poorly understood population dynamics (Adams and Bailey 1982). Their selection of cliffs evolutionarily decreased their predation pressure, but use of these sites carries with it an increased risk of death or injury due to falls and rock slides (Johnson 1983). Characteristically rugged, this species has shown in the past the ability to rapidly colonize new territory (Hayden 1984) and quickly disappear in others (Kuch 1977).

Native mountain goat populations of the Washington Cascades have decreased over the last several decades (Côté & Festa-Bianchet 2003). Some rough estimates suggested declines as much as 70% over the last forty years (Rice pers. comm.). In some locales that once had dozens of goats, for instance the wintering grounds at Penders Canyon, recent surveys have found few small bands or no goats at all. This decline has resulted in a major reduction of the permitted hunt. Concern over the population decline also prompted studies investigating the reasons behind this trend. Possible explanations for the population decline include: over hunting, increased recreational disturbances, increased cougar *Felis concolor* populations, disease, population fragmentation, loss of genetic viability, habitat loss, climate change and the combination of multiple stressors.

Most previous work on mountain goat habitat has focused on summer months. Severe weather and logistical issues has made it problematic to address seasonal variation in habitat use in any systematic fashion. Understanding total year round available habitat can assist land-use managers and applied conservation strategies designed to assist in mountain goat recovery. To augment the existing, largely summer, anecdotal accounts of mountain goat habitat (Gross *et al.* 2002), I have developed a year round GIS habitat model based on an elevation profile of GPS collared mountain goats. The objective of this was to improve the accuracy and precision of previous modeling efforts (Johnson & Cassidy 1997), incorporate a GPS bias correction model and to designate the largely unknown (Côté and Festa-Bianchet 2003) lower elevation habitats; areas of critical importance to over wintering success. It is these lower reaches of habitat that often fall within range of and were most susceptible to direct disturbance from anthropogenic sources. Individual accounts of past human activities suggested that such disturbances have lead to extirpation of local populations through destruction of over wintering sites. This research contributed to establishment of an ecological base line by which future investigations of mountain goat ecology and population trends may measure.

In this chapter, I developed a series of statistical models to identify potential mountain goat habitat on the western side of the Cascade Mountain Range in Washington State. These habitat models are based on location data collected over a two-year period from 39 GPS collared animals. These habitat models incorporate the GPS bias correction effort described in Chapter One. The resulting maps provide insights on the status of potential mountain goat habitat and will contribute to more effective management and possible recovery of the species in Washington State.

.

Materials and Methods

Capture and Collars

WDFW captured and administered care and supervision of study animals in accordance with American Society of Mammalogists' guidelines. Mountain goats were captured via aerial and ground-based darting with 0.4-0.5 cc Carfentanil or 50-70 mg xylazine hydrochloride mixed with 0.15-0.25 mg of opiate A3080 and reversed with 3.0 cc Naltrexone or 4.0 cc Tolazine, respectively. The 39 captured individuals were outfitted with GPS telemetry collars (GPS plus collar v6, Vectronic-Aerospace GmbH, Berlin, Germany) scheduled to record a fix every 3 hours for a period of 2 years. Initially, nine of the captured animals' collars recorded fixes on a 5-hour interval accounting for 10% of the data used in this analysis. Most of these five-hour intervals were reprogrammed within 6 months. Three animals were recaptured and re-collared after hardware failure. Seven collars failed and animals were not re-collard prior to two full years worth of data collection. Six study animal mortalities occurred during the 2-year period, mostly from unknown causes. Use of data from multiple years was intended to reduce the impact of inter-annual habitat selection due to weather. The winter of 2004-05 had very low snow pack throughout most of the Cascades and the winter of 2005-06 had snow packs that were slightly higher than the long-term average (USDA 2006)

Data Analysis

I created eight-habitat selection models based on elevation ranges employing the use-availability design type II sampling protocol SP-A (Manly *et al.* 2002, Keating & Cherry 2004). I used weighted logistic regression with Akaike's Information Criteria (AIC) to select each of the most parsimonious model based on a subset of models. I modeled the probability of a mountain goat location (π) as:

$$\pi = \frac{\exp(ß_0 + ß_1 X_1 + ß_2 X_3 + \ldots + ß_p X_p)}{1+\exp(ß_0 + ß_1 X_1 + ß_2 X_3 + \ldots + ß_p X_p)} \qquad \text{eqn. 3}$$

The weighting factor accounted for GPS data loss due to topographic and vegetation obstructions of satellite signals using the inverse of the GPSPAR developed from Chapter One. I also generated parameter estimates for the selected models without the weighting factor to gauge the influence of the bias correction factor. I calculated cut points based on the predicted probability at the convergence of the cumulative number of goats points versus the cumulative number of available points and developed classification accuracies from these.

Assumptions:

The use-availability design protocols also presumed a number of assumptions regarding the study design that used measurable attributes of resource use. The stated assumption, "animals have free and equal access to all available locations" (Manly *et al.* 2002) required consideration and ultimately violating. Mountain goats inhabiting relatively small ranges with few, if any, long range dispersals could not have equal access to all locations in the entire Cascades mountain range. To model such a situation, I had to generate available locations based upon some reasonable limitation of each individual animals theoretical movements. This however, precluded modeling the entire study area as a whole range for the species. I therefore compromised, and split the available sites into northern and southern regions divided along the Interstate 90 corridor. This split the data set into 8 subsets, based on the four elevation bands in the north and south, which I modeled individually. Delineation of elevation quartiles was made prior to the division of habitat into two regions. I clustered an equal number of random points to mountain goat points based on this north south division. In other words, regarding the stated assumption about free and equal access, mountain goats in the northern half of the study area have access to all points north of I-90 and likewise for the south. This certainly remained a violation of the assumption and ecological reality but reduced computational loads and the number of data sets required to model a species wide assessment of potential habitat.

The repeated measure of individual animals also violated the assumption of independence of observations. I attempted to model the correlation structure of the intra-cluster structure of GPS waypoints of collared animals to account for this. I wanted to use a non-linear mixed model during model selection to account for this clustering of observations by clustering the individual animal as a random effect. Each cluster of individual animal locations was paired with an equal number of available sites in the cluster. After selecting the most parsimonious model I then wanted to use the PROC GEN MOD command in SAS to model the correlation structure of the waypoints with a generalized estimating equation (GEE) and generate robust standard errors and modified parameter estimates. The amount of random effects variability in the datasets however, failed to achieve quadrate accuracy during model selection and failed to estimate variance with a GEE with either auto-regressive or exchangeable correlation structure. I therefore retained the initial parameter estimates generated with ordinary logistic regression for habitat modeling while recognizing the inherent flaws with the standard error estimates.

GIS habitat predictor variables

A series of predictor variables were developed to describe the vegetation and topographic characteristics of the study area. For each goat location, I extracted GIS data at one spatial scale for inclusion in the habitat analysis, 625 m^2 (75 m x 75 m square extraction window). I opted to use a 625 m^2 extraction window recognizing that over the three hour GPS sampling interval, mountain goats likely selected habitats at a scale much larger than the finest resolution of available satellite imagery, 25 m. This scale also encompassed more of the GPS inaccuracies.

As described in Chapter One, I used the IVMP (O'neil *et al*. 2002) data layers to create independent vegetation variables. I created six classes of total vegetative cover: 0-20%, 20-40%, 40-60%, 60-80%, 80-100% total cover and areas classified as rock and ice.

I broke the QMD data layers into four classes: No cover, 0-30cm, 31-60cm and 61-190cm. The CC layer I classified into three discrete categories: 0-30%, 30-70% and 71-100%. I did not select even intervals for the CC due to prior definitions of areas with no cover in the QMD layer as specified by the IVMP. The IVMP considers areas with less than 30% CC as areas with a QMD of 0. This way the lowest definition of CC remained consistent with the QMD layer. I did not include any variables representing broadleaf coverage in the analysis. The final vegetation variables used for model creation included the mode and variety of pixels classified by TVC, QMD and CC for each square extraction window. I treated the vegetation variables as categorical represented by implied dummy variables.

I derived topographic predictor variables from a 10 m DEM masked to the same spatial extent and resampled to the same pixel size as the western cascades of Washington IVMP data set (25 m). I created slope and aspect layers with Spatial Analyst (ESRI 2004) using the surface tool set. In the analysis, I used slope as a continuous data directly exported from the GIS. Considering the circular nature of aspect and the possible importance of this as a factor in mountain goat habitat selection, I opted to transform aspect into two distinct continuous covariates (Gross *et. al.* 2002). I used the cosine and sine of aspect, in radians, to model whether or not mountain goats show selective use of slopes from north to south and east to west.

The distance to escape terrain data layer involved a few additional calculations. I defined escape terrain as areas with slopes greater than 35° based on an average of previously reported values (Fox and Taber 1981; Johnson 1983; Varley 1994; Fox 1989; Gross *et al*. 2002). I used a slope layer created at the 10 m resolution to and reclassified areas with slopes greater than 35° as escape terrain or not. I made this distinction prior to reclassifying the pixels to the 25 m cell size in order to retain the finest possible resolution for defining distance to escape terrain. The 10 m pixel size is simply too computationally intensive to used for the entire model, despite having a greater precision. I then used the Euclidean distance tool to calculate the distance from the center of each pixel in the raster file to the nearest pixel of escape terrain. The final topographic predictor variables available for model building came from a 3 x 3 pixel extraction window and included mean degree slope, standard deviation of slope, elevation (m), sine and cosine of aspect and distance to escape terrain (m).

Results

Initially, I wanted to define seasonal habitats used by mountain goats in the sense of a calendar driven definition of seasons. In other words, during the winter goats inhabited a particular regions and during the summer and another region during the winter. Describing habitat in this framework however, failed for a number of reasons. Some animals changed elevation frequently, others much less. Some animals went high on the slopes of volcanoes while others did, or could not, given the geomorphic setting that they occupied. Comparing animals revealed that many may have moved lower at the same time in the fall, but using any sort of average date, showed an earlier change for those that started higher (Fig. 7). Apparently, some individuals had access to low elevation habitats and others simply did not.

In addition, the whole phenomenon likely hinged on weather patterns, and only worked in a broad sense because of the relationship between season and weather. The variability of weather within a season and between years created part of the problem. Natural history of the mountain goat suggested that animals respond to weather in their use of different seasonal habitats. So, if an animal moved to high ground in March because of "good weather" and back down in April during "bad weather", how does fit into the notion of calendar driven seasons? Did the goat use summer habitat in March and winter habitat in April? Or does the "winter" habitat include the March locations? If the animal went to "summer" habitat during the mild spell, then returned to "winter" habitat with the return of poor weather then partitioning seasons by date defied efficient data management, analysis and ecological relevant partitioning of habitat ranges.

Instead, I looked at the habitat usage by elevation. In this way, the habitat modeling predicted that when a mountain and goat was at any give elevation its selection of habitats was based on these different characteristics. When a goat responded to a weather driven phenomenon and moved to a different elevation band, the modeling scheme accounted for these intra-seasonal (in a calendar defined) changes in habitat use. The final modeling scheme then predicted four ranges of habitat use based on elevation.

The use-availability experimental design in habitat selection modeling called for a set of random or available points. I used Hawth's analysis tools (Beyer 2004) to generate random points in accordance with the elevation quartiles of GIS mountain goats locations. I bound the lower limit of the first quartile of random points with a conservative estimate of 300 m based on the lowest extracted GIS elevation of a successful GPS fix from a mountain goat (322 m). I defined the upper limit of the 4^{th} quartile random points at 3100 m and maintained a 1:1 ratio of individual goat locations to random points in each quartile.

I acquired 86,826 GPS locations from the 39 collared mountain goats. The elevation distribution of these points based on GIS elevations rather then the recorded GPS elevations followed a Gaussian curve (Fig. 8). The eight data subsets had a range of total number of waypoints from 3843 in the lowest elevation band in the southern Cascades to 17,751 waypoints in the northern cascades lowest elevation quartile. The 4 northern cascades elevation bands constituted 51,881 waypoints while the 4 southern subsets tallied 34,945 waypoints. In the northern region, each quartile contained locations from 21 animals, while the southern region had 11 animals in the 1st quartile, 15 in the 2^{nd} and 16 in both the 3rd and 4th quartile.

From these GIS extracted elevations I determined the 1^{st} quartile at 1187 m, the median at 1455 m and the 3^{rd} quartile at 1670 m. The upper elevation of the 4^{th} quartile was bounded at 3100 m above which no mountain goat locations were recorded. The distribution of goat locations by month within these quartiles follows expected trends of seasonal goat movement (Fig. 9).

The most parsimonious models for the eight datasets based on weighted goat locations followed similar patterns of variable inclusion. The global model along with two similar models, one excluding the first class of QMD and the other the variety of QMD classes in the extraction window, constituted the highest ranked subset of models according to the AIC scores (Table 9.0) for all the datasets. The selected models were not the same for the 1st and 4th elevation quartiles across the two regions. The 3rd and 2nd quartiles had the same model parameters in both regions. All of the models included the topographic variables distance to escape terrain, both measures of aspect, elevation, slope and standard deviation of slope. The vegetation variables included in the models varied slightly but all included each category of variable QMD, conifer cover and total vegetation cover (Table 9.1-9.8). Empirical cumulative frequency distributions of topographic predictor variables showed selection by goats for distance to escape terrain and slope (Fig. 10).

The cut points between the number of available sites and mountain goat sites were lower for the un-weighted habitat map (Table 10). Classification accuracies based on these cut points showed the weighted maps had a slightly better ability to differentiate mountain goat habitat from non-habitat in four of the eight datasets and virtually equal classifications in the remaining four. Area under the receiver operating curve for each of the eight weighted models exceeded 0.70 (Table 10) based upon independent data.

The final habitat map displays the continuous probability of potential mountain goat habitat taking into account the GPS bias correction factor across the Western Cascades Province (Fig. 11). Taking the average cut point for all quartiles from the weighted ($\bar{x}$ = 0.596) and un-weighted map ($\bar{x}$ = 0.575) and reclassifying all probabilities as habitat or not indicated a total of 253,638 ha and 249,715 ha of total available mountain goat terrain respectively. This amounted to 9.2% and 9.0% of the total study area.

Discussion

The final habitat maps shows in one data layer, the predicted probability of the landscape being mountain goat habitat or not taking into account a small GPS bias correction factor developed in Chapter one. The differentiation of available sites from north to south across the mountain range as well as the four elevation quartiles used to model habitat created eight distinct models and habitat mapping regions. These eight were mosaiced into one final map interpreted as probability of habitat selection based on elevation use. Thus at any given landscape, elevation the probability of the site being mountain goat terrain may be inferred. Using the optimal cut points yields the best classification accuracy of the landscape being habitat or not, but adjusting these points based on management objectives will alter the maps towards either a more or less conservative estimate of mountain goat habitat.

The final map was consistent with population distribution patterns of mountain goats throughout large portions of the western Cascades. The regions circumnavigating around Mt. Baker (Fig. 12) showed high potential habitat in areas known to contain 300-400 mountain goats. The Three Fingers-Whitehorse mountain chain also clearly included substantial amount of habitat (Fig. 13). The mountain goat habitat in this region appears to lack connectivity to other nearby habitat although there does appear to be some connectivity to the southeast. Even in this direction there is a major drainage system that separates the Three Fingers-Whitehorse habitat complex from the Glacier Peak habitat complex to the east. Mount Rainier (Fig. 14) also has lots of habitat along its slopes with a distinctly more sinuous structure. The habitat patches appeared longer and more narrow than those around Mt. Baker and not as well connected. This most likely stemmed from the fact Mt. Rainer stands much larger then Mt. Baker and consequently has habitat patches spread out across greater distances and much further away from one another. This area currently supports a large population of mountain goats.

The data layer also displayed some high probabilities of potential mountain goat habitat in areas with few or no populations. In particular, the areas east of Mt. Baker towards the North Cascades National Park and the Pickett Range have some of the darkest and most obvious patches of habitat (Fig. 15). This region however, does not support a strong population of mountain goats. The central Cascades also have quite a bit of habitat but currently do not support strong populations of mountain goats possibly to large harvest in the past (Fig. 16). The southern Cascades, from Goat Rocks Wilderness Area to Mt. Adams and Mt. St. Helens (Fig. 17), show more disjointed and not nearly as much high quality habitat as the Northern Cascades although they do support mountain goat populations.

The trends in elevation use follow expected ecological patterns. There was high use of the fourth elevation quartile during July, June and August after a quick transition up from the peak usage in lower quartiles. Downward movements progressed more slowly in the end of the summer and fall months. The lowest quartile had the highest usage during the first three and last two months of the year. This fit with expected patterns of elevation changes across seasons and supported partitioning the data and modeling habitat by elevation quartiles to capture seasonal trends.

Weighting each of the goat location on the basis of GPS PAR did not appear to have much effect on the habitat models. The slightly lower cut points developed with models not using the weighting factor to offset GPS PAR resulted in slightly lower classification accuracies across four of the eight datasets. The difference in cut points and accuracies however, was virtually negligible in these four models. The total area of potential habitat delineated by each set of models was similar. The greater total area of habitat based on the weighted model's mean cut points suggested the bias correction factor accounted for some habitat's where detection of study animals may have been low.

The small difference between the weighted and un-weighted models may result from at least two different factors. First, the predictive power of the GPS bias correction model from Chapter One was comparable to that reported in other studies (Rempel *et al.* 1995; Deckert & Bolstad 1996; Edenius 1997; Dussault *et al.* 1999; Gamo & Rumble 2000; Licoppe 2001; Rodgers 2001; D'Eon *et al.* 2002; Taylor 2002; Di Orio *et al.* 2003; Frair *et al.* 2004; Cain *et al.* 2005; Sager 2005) but it was still relatively low. Second, the effect of bias in GPS PAR may have been minimized because I developed separate habitat models for each elevation band. Had I developed a single model using location data from all elevation bands, the effect of bias in GPS PAR may have resulted in a larger difference between weighted and un-weighted habitat models.

In both the north and south, the classification accuracy and area under the receiver-operating curve improved in lower elevation quartiles. This was a counterintuitive result. I expected the higher elevation habitats to be clearly delineated while the lower elevation habitats would be more difficult to define. This may be a consequence of the lower elevation quartiles classifying more terrain as habitat even thought they do not have good access to high elevation habitats while the areas actually used by mountain goats at low elevations may be quite limited. The higher elevation habitats may have lower classification accuracies due to the availability of much more moderate habitat not necessarily used when goats at high elevations may be selecting the most precipitous terrain. There also may have been more contaminated controls (Keating & Cherry 2004) at the higher elevations then at the lower elevation bands.

The habitat models showed similar patterns of variable inclusion across all eight datasets. In each model, all the topographic predictor variables were retained as well as some measure of all the three types of vegetation predictor variables. The most parsimonious models were the global model or the global model with the exclusion of one variable. These models excluded the first QMD class or the variety of QMD classes found in the 9 x 9 pixel square extraction window.

Examining the results from north to south, the variable representing areas of rock and ice (Table 9.1-9.8 *tvc6*) shows a strong difference between these regions. In the southern models all the parameter estimates have negative values while the northern regions all show positive estimates. Distance to escape terrain also had negative parameter estimates in all but one data set, the first quartile of the southern region. This suggested that animals at the lowest observed elevations in this region may have shown some selection for habitats away from slopes greater then 35°. This might reflect some long distance dispersal movements recorded in that region, varying topographic features, or simply a failure of the model to capture the random effects error structure with properly robust confidence intervals.

The violation of certain assumptions regarding the habitat modeling process and choices therein has created some unavoidable error in modeling methodology. The lack of enough variation, or small random effects size resulted in the choice of ordinary logistic regression that failed to account for the lack of independence between data points acquired from a single study animal. The use of the PROC GLIMMIX command in SAS may provide the ability to correctly account for these random effects and lack of independence in future modeling efforts. The largest discrepancy between a model accounting for random effects was in the standard error and resulting confidence intervals. The final habitat models (Table 9.1-9.8) have much too narrow confidence because of the failure to model such small random effects. Parameter estimates may have varied slightly as well as some Chi-squared test statistics.

The final habitat maps generated in this analysis lay the groundwork for a more detailed assessment of available mountain goat habitat in the western Cascades. Future work should look at the spatial orientation and connectivity of habitat patches. Identifying the largest patches of contiguous habitat would help in the success of a relocation effort and establishment of viable populations with suitable access to terrain and other animals.

To get a full picture of the habitat available to the entire Cascade population of mountain goats the eastern Cascades of Washington also need a similar habitat model.

Based on the relatively small influence of the weighting factor on the western cascades where I expected much lower GPS PAR, I would seriously consider the merits of incorporating the weighting factor in the eastern habitat models. I expect much higher rates of GPS PAR on the east side and consequently less data loss from collared wildlife. A more prudent option to account for GPS bias might be to develop some heuristic algorithms to estimate individual missed fixes based on movement parameters. East side habitat mapping should also carefully consider the lack of independence between success fixes. As mentioned before, the GLIMMIX procedure may handle more easily a mixed model structure. There is no need to run an initial logistic regression and then a non-linear mixed model. The GLIMMIX command should handle everything in one step. Alternatively, considering a different statistical design may account for the lack of independence by modeling each animal individually and extrapolating results to the entire range.

In my opinion, the results, the amount of fieldwork, the required methodological development and data analysis for developing the bias correction model did not provide a large return on the investment. The weighted and un-weighted habitat maps appeared almost identical, although a more thorough analysis might provide greater insight to the degree of similarity. Considering the applied nature of the map and ability to change cut points based on management objectives to define mountain goat habitat, the weighting factor most likely will be a mute point with even a slight shift in cut points.

Tables

Table 9.0: The models, number of parameters (K), AIC scores, delta AIC scores and AIC weights of the highest ranked models for the eight datasets used to construct the predicted potential mountain goat habitat maps for each elevation quartile (Q1,Q2,Q3 &Q4).

North		**Q1**			**Q2**			**Q3**			**Q4**		
model	*K*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*
global	20	13944	0	1	18353	2	0.367879	19156	1	0.606531	13017	2	0.367879
global w/o qmd1	19	13985	41	1.25E-09	18351	0	1	19163	8	0.018316	3029	14	0.000912
global w/o qmd variety	19	14004	58	2.54E-13	18372	21	2.75E-05	19155	0	1	13015	0	1

South		**Q1**			**Q2**			**Q3**			**Q4**		
model	*K*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*
global	20	1538	1	0.606531	5276	1	0.606531	8677	1	0.606531	21595	0	1
global w/o qmd1	19	1537	0	1	5275	0	1	8685	9	0.011109	21620	25	3.73E-06
global w/o qmd variety	19	1546	9	0.011109	5315	40	2.06E-09	8676	0	1	21610	15	0.000553

Table 9.1-9.8: The final habitat models for the eight datasets used to model predicted potential mountain goat habitat across the western Cascades of WA, divided by elevation quartiles and a northern (Table 9.1-9.4) and southern (Table 9.5-9.8) region.

NORTH:

Table 9.1: First Quartile (Lowest Elevation)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-8.8672	0.2129	-9.2846	-8.4499	1734.24	<.0001
aspcos	1	-0.9412	0.0362	-1.0121	-0.8702	675.96	<.0001
aspsin	1	-0.4560	0.0331	-0.5208	-0.3912	190.18	<.0001
elev	1	0.0033	0.0001	0.0031	0.0035	805.80	<.0001
slope	1	0.1131	0.0033	0.1067	0.1196	1179.17	<.0001
slope_stdv	1	0.1562	0.0079	0.1408	0.1717	391.41	<.0001
d2et	1	-0.0095	0.0010	-0.0114	-0.0075	90.11	<.0001
tvc2	1	0.1816	0.1207	-0.0550	0.4182	2.26	0.1326
tvc3	1	0.1071	0.1085	-0.1055	0.3198	0.97	0.3235
tvc4	1	-0.5672	0.1092	-0.7812	-0.3533	27.00	<.0001
tvc5	1	-1.3474	0.1185	-1.5796	-1.1152	129.35	<.0001
tvc6	1	1.3612	0.3047	0.7639	1.9585	19.95	<.0001
tvc_variety	1	0.7106	0.0307	0.6504	0.7708	535.28	<.0001
qmd1	1	-0.6072	0.0938	-0.7910	-0.4234	41.93	<.0001
qmd2	1	-0.2758	0.0951	-0.4623	-0.0893	8.40	0.0037
qmd3	1	-0.5749	0.0867	-0.7448	-0.4049	43.95	<.0001
qmd_variety	1	0.2630	0.0304	0.2034	0.3226	74.77	<.0001
cc2	1	0.5515	0.0783	0.3981	0.7049	49.66	<.0001
cc3	1	0.5146	0.0938	0.3307	0.6985	30.08	<.0001
cc_variety	1	-0.1001	0.0398	-0.1780	-0.0222	6.34	0.0118

Table 9.2: Second Quartile

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-0.8658	0.3472	-1.5462	-0.1853	6.22	0.0126
aspcos	1	-0.8536	0.0298	-0.9120	-0.7953	821.43	<.0001
aspsin	1	-0.3669	0.0283	-0.4224	-0.3114	167.81	<.0001
elev	1	-0.0014	0.0002	-0.0019	-0.0010	38.54	<.0001
slope	1	0.0508	0.0029	0.0451	0.0565	304.95	<.0001
slope_stdv	1	0.0764	0.0062	0.0643	0.0885	153.00	<.0001
d2et	1	-0.0170	0.0011	-0.0192	-0.0149	233.16	<.0001
tvc2	1	1.1969	0.0851	1.0302	1.3637	197.90	<.0001
tvc3	1	0.2065	0.0774	0.0548	0.3582	7.12	0.0076
tvc4	1	-0.1514	0.0794	-0.3071	0.0042	3.64	0.0566
tvc5	1	-0.9400	0.0842	-1.1051	-0.7749	124.56	<.0001
tvc6	1	2.3258	0.1123	2.1057	2.5460	428.69	<.0001
tvc_variety	1	0.4480	0.0238	0.4014	0.4946	355.24	<.0001
qmd2	1	-0.4754	0.0618	-0.5966	-0.3543	59.14	<.0001
qmd3	1	-1.0003	0.0546	-1.1074	-0.8932	335.32	<.0001
qmd_variety	1	0.1449	0.0275	0.0910	0.1989	27.71	<.0001
cc2	1	0.2410	0.0596	0.1241	0.3579	16.33	<.0001
cc3	1	0.4502	0.0725	0.3082	0.5923	38.60	<.0001
cc_variety	1	-0.1994	0.0336	- 0.2653	-0.1335	35.21	<.0001

Table 9.3: Third Quartile

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	0.2077	0.4687	-0.7110	1.1264	0.20	0.6577
aspcos	1	-0.6919	0.0302	-0.7511	-0.6327	524.32	<.0001
aspsin	1	-0.3439	0.0269	-0.3966	-0.2912	163.62	<.0001
elev	1	-0.0018	0.0003	-0.0023	-0.0012	38.54	<.0001
slope	1	0.0557	0.0026	0.0506	0.0607	463.72	<.0001
slope_stdv	1	0.0788	0.0059	0.0673	0.0902	181.26	<.0001
d2et	1	-0.0033	0.0008	-0.0048	-0.0018	19.40	<.0001
tvc2	1	0.7059	0.0631	0.5822	0.8296	125.08	<.0001
tvc3	1	0.3897	0.0620	0.2682	0.5113	39.49	<.0001
tvc4	1	-0.0473	0.0695	-0.1835	0.0888	0.46	0.4956
tvc5	1	-0.5504	0.0824	-0.7119	-0.3889	44.60	<.0001
tvc6	1	0.9908	0.0721	0.8494	1.1322	188.71	<.0001
tvc_variety	1	0.1255	0.0217	0.0829	0.1680	33.44	<.0001
qmd1	1	-0.1845	0.0778	-0.3370	-0.0320	5.62	0.0178
qmd2	1	-1.1555	0.1006	-1.3526	-0.9584	132.03	<.0001
qmd3	1	-1.1734	0.0833	-1.3366	-1.0103	198.65	<.0001
cc2	1	-0.1561	0.0536	-0.2611	-0.0511	8.49	0.0036
cc3	1	-0.0794	0.0710	-0.2185	0.0596	1.25	0.2629
cc_variety	1	-0.0452	0.0325	-0.1089	0.0184	1.94	0.1638

Table 9.4: Fourth Quartile (Highest Elevation)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	7.2777	0.3223	6.6460	7.9095	509.83	<.0001
aspcos	1	-0.9675	0.0398	-1.0454	-0.8895	592.00	<.0001
aspsin	1	-0.2833	0.0326	-0.3471	-0.2195	75.72	<.0001
elev	1	-0.0045	0.0002	-0.0048	-0.0042	840.12	<.0001
slope	1	0.0053	0.0030	-0.0005	0.0111	3.16	0.0756
slope_stdv	1	0.0456	0.0068	0.0322	0.0590	44.44	<.0001
d2et	1	-0.0086	0.0009	-0.0103	-0.0068	89.05	<.0001
tvc2	1	0.7568	0.0675	0.6246	0.8890	125.86	<.0001
tvc3	1	0.6767	0.0729	0.5339	0.8195	86.23	<.0001
tvc4	1	0.0058	0.0958	-0.1818	0.1935	0.00	0.9513
tvc5	1	-0.8941	0.1524	-1.1928	-0.5953	34.40	<.0001
tvc6	1	0.7940	0.0646	0.6673	0.9207	150.84	<.0001
tvc_variety	1	-0.0376	0.0276	-0.0917	0.0165	1.85	0.1736
qmd1	1	-0.5551	0.1480	-0.8452	-0.2650	14.06	0.0002
qmd2	1	-2.1120	0.2978	-2.6957	-1.5283	50.29	<.0001
qmd3	1	-1.8249	0.2121	-2.2406	-1.4091	74.02	<.0001
cc2	1	0.1039	0.0698	-0.0329	0.2407	2.21	0.1368
cc3	1	0.4817	0.1019	0.2820	0.6814	22.34	<.0001
cc_variety	1	0.0697	0.0424	-0.0133	0.1527	2.71	0.1000

SOUTH:

Table 9.5: First Quartile (Lowest Elevation)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr >ChiSq
Intercept	1	-18.5027	0.7409	-19.9548	-17.0506	623.69	<.0001
aspcos	1	-0.4339	0.1154	-0.6602	-0.2076	14.13	0.0002
aspsin	1	-0.1748	0.0957	-0.3624	0.0127	3.34	0.0677
elev	1	0.0074	0.0005	0.0065	0.0083	258.35	<.0001
slope	1	0.2501	0.0099	0.2307	0.2696	637.84	<.0001
slope_stdv	1	0.0805	0.0242	0.0331	0.1280	11.05	0.0009
d2et	1	0.0009	0.0008	-0.0006	0.0024	1.41	0.2350
ric2	1	0.6018	0.4664	-0.3122	1.5159	1.67	0.1969
ric3	1	0.2663	0.3925	-0.5030	1.0356	0.46	0.4975
ric4	1	-0.2836	0.3583	-0.9859	0.4187	0.63	0.4287
ric5	1	0.1078	0.3636	-0.6048	0.8205	0.09	0.7668
ric6	1	-21.7808	34232.09	-67115.4	67071.88	0.00	0.9995
rockice_variety	1	0.3230	0.1030	0.1211	0.5250	9.83	0.0017
qmd2	1	-0.2244	0.2012	-0.6187	0.1699	1.24	0.2647
qmd3	1	-0.0861	0.2052	-0.4883	0.3162	0.18	0.6750
qmd_variety	1	0.3518	0.1011	0.1536	0.5499	12.11	0.0005
con2	1	0.0431	0.2628	-0.4720	0.5582	0.03	0.8697
con3	1	0.5695	0.3219	-0.0614	1.2004	3.13	0.0769
con_variety	1	0.4532	0.1300	0.1985	0.7079	12.16	0.0005

Table 9.6: Second Quartile

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-16.4693	0.6912	-17.8241	-15.1145	567.68	<.0001
aspcos	1	-0.1952	0.0601	-0.3131	-0.0773	10.53	0.0012
aspsin	1	-0.2791	0.0499	-0.3770	-0.1812	31.22	<.0001
elev	1	0.0053	0.0005	0.0044	0.0062	136.78	<.0001
slope	1	0.2412	0.0063	0.2288	0.2537	1449.08	<.0001
slope_stdv	1	0.1095	0.0115	0.0870	0.1319	91.20	<.0001
d2et	1	-0.0014	0.0011	-0.0036	0.0008	1.67	0.1967
tvc2	1	0.0250	0.2084	-0.3834	0.4335	0.01	0.9044
tvc3	1	-0.4009	0.1729	-0.7398	-0.0620	5.38	0.0204
tvc4	1	-0.9617	0.1824	-1.3192	-0.6042	27.80	<.0001
tvc5	1	-0.8973	0.1850	-1.2599	-0.5346	23.52	<.0001
tvc6	1	-1.4221	0.5421	-2.4846	-0.3597	6.88	0.0087
tvc_variety	1	0.1729	0.0507	0.0736	0.2722	11.63	0.0006
qmd2	1	-0.6154	0.1095	-0.8299	-0.4008	31.60	<.0001
qmd3	1	-0.4339	0.1024	-0.6346	-0.2333	17.97	<.0001
qmd_variety	1	0.3757	0.0532	0.2714	0.4800	49.88	<.0001
cc2	1	0.1840	0.1569	-0.1236	0.4915	1.37	0.2410
cc3	1	0.1727	0.1818	-0.1837	0.5290	0.90	0.3422
cc_variety	1	0.3035	0.0647	0.1767	0.4302	22.02	<.0001

Table 9.7: Third Quartile

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-7.1235	0.7644	-8.6218	-5.6252	86.83	<.0001
aspcos	1	-0.0911	0.0511	-0.1911	0.0090	3.18	0.0745
aspsin	1	-0.4833	0.0404	-0.5624	-0.4042	143.36	<.0001
elev	1	0.0019	0.0004	0.0010	0.0028	18.23	<.0001
slope	1	0.1324	0.0050	0.1226	0.1423	694.85	<.0001
slope_stdv	1	0.1364	0.0088	0.1192	0.1536	242.52	<.0001
d2et	1	-0.0108	0.0015	-0.0137	-0.0080	55.67	<.0001
tvc2	1	-0.9992	0.1358	-1.2653	-0.7330	54.13	<.0001
tvc3	1	-1.5048	0.1220	-1.7439	-1.2656	152.09	<.0001
tvc4	1	-1.5628	0.1317	-1.8209	-1.3046	140.76	<.0001
tvc5	1	-1.7165	0.1435	-1.9976	-1.4353	143.17	<.0001
tvc6	1	-4.4578	0.4904	-5.4190	-3.4966	82.63	<.0001
tvc_variety	1	0.2342	0.0395	0.1568	0.3116	35.17	<.0001
qmd1	1	-0.3687	0.1311	-0.6257	-0.1118	7.91	0.0049
qmd2	1	-0.5861	0.1288	-0.8386	-0.3335	20.69	<.0001
qmd3	1	-0.5310	0.1212	-0.7686	-0.2935	19.20	<.0001
cc2	1	-0.1024	0.1174	-0.3325	0.1277	0.76	0.3833
cc3	1	-0.0691	0.1385	-0.3405	0.2023	0.25	0.6177
cc_variety	1	0.3110	0.0512	0.2106	0.4113	36.87	<.0001

Table 9.8: Fourth Quartile (Highest Elevation)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-1.3808	0.2082	-1.7890	-0.9727	43.97	<.0001
aspcos	1	-0.2119	0.0294	-0.2696	-0.1542	51.82	<.0001
aspsin	1	-0.4271	0.0248	-0.4757	-0.3786	297.45	<.0001
elev	1	-0.0004	0.0001	-0.0005	-0.0002	15.00	0.0001
slope	1	0.0683	0.0023	0.0638	0.0728	881.86	<.0001
slope_stdv	1	0.0710	0.0055	0.0603	0.0818	167.47	<.0001
d2et	1	-0.0029	0.0003	-0.0035	-0.0023	101.10	<.0001
tvc2	1	-0.8212	0.0756	-0.9694	-0.6731	118.04	<.0001
tvc3	1	-1.0508	0.0663	-1.1807	-0.9209	251.24	<.0001
tvc4	1	-1.2842	0.0792	-1.4393	-1.1290	263.22	<.0001
tvc5	1	-1.5925	0.0959	-1.7804	-1.4045	275.74	<.0001
tvc6	1	-1.2844	0.0601	-1.4022	-1.1667	457.26	<.0001
tvc_variety	1	0.1668	0.0211	0.1255	0.2081	62.71	<.0001
qmd1	1	-0.4918	0.1016	-0.6909	-0.2927	23.44	<.0001
qmd2	1	-0.4929	0.0995	-0.6880	-0.2979	24.53	<.0001
qmd3	1	-0.2592	0.0837	-0.4233	-0.0952	9.59	0.0020
qmd_variety	1	0.1410	0.0304	0.0814	0.2006	21.47	<.0001
cc2	1	-0.0489	0.0660	-0.1782	0.0805	0.55	0.4590
cc3	1	0.1502	0.0903	-0.0267	0.3271	2.77	0.0960
cc_variety	1	0.1540	0.0349	0.0857	0.2223	19.53	<.0001

Table 10: Area under the receiver operating curve (AUC) for the weighted models, cut points and accuracy of correctly classified independent mountain goat locations for the mountain goat datasets divided into four elevation bands and two geographic regions, north and south cascades of Washington, with and without a weighting factor incorporated to account for GPS bias.

Cascades	Elevation		Weighted		Un-weighted	
Region	Quartile	AUC	cut point	accuracy	cut point	accuracy
North	1st	0.96	0.63	0.89	0.60	0.89
	2nd	0.88	0.60	0.80	0.56	0.79
	3rd	0.82	0.56	0.75	0.55	0.74
	4th	0.77	0.54	0.69	0.53	0.69
South	1st	0.99	0.60	0.95	0.59	0.95
	2nd	0.97	0.63	0.93	0.59	0.92
	3rd	0.94	0.64	0.87	0.62	0.87
	4th	0.84	0.54	0.77	0.54	0.76

Figures

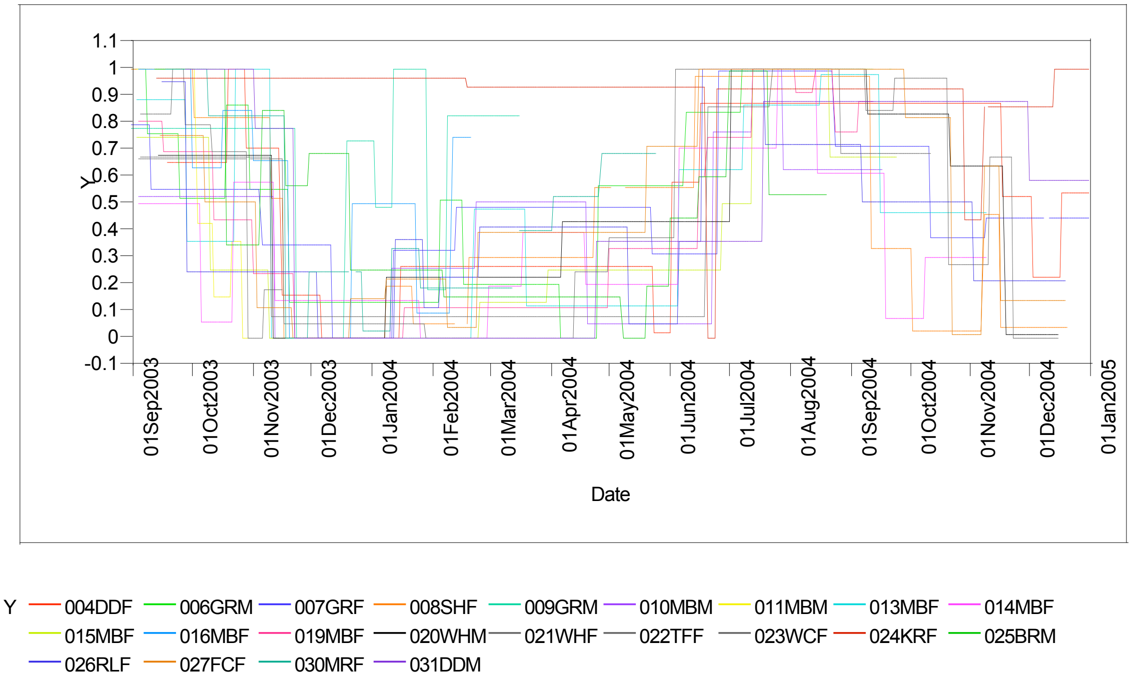

Fig. 7. Proportional elevation shifts in mountain goats from different locations showing the complexities associated with defining calendar-driven mountain goat seasons based on elevation movements.

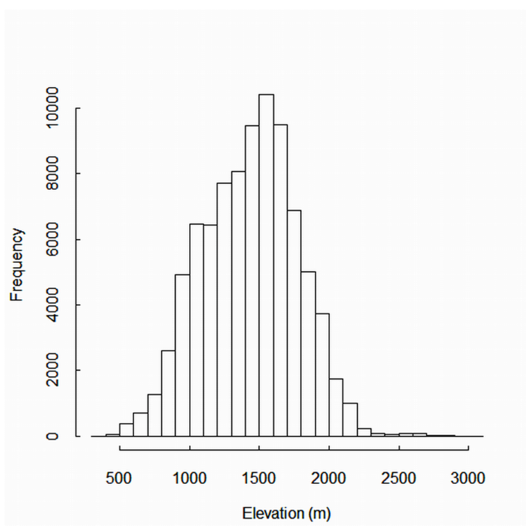

Fig. 8. Histogram of all GIS-derived mountain goat elevations from GPS points showing a Gaussian distribution and the range of observed values (Frequency = Percentage of Fixes).

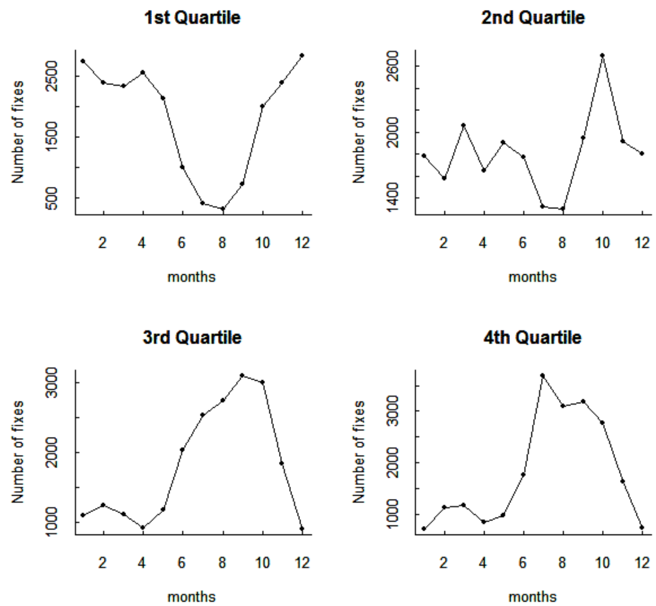

Fig. 9. Distribution of mountain goat locations acquired by month within each elevation quartile: 1st (300-1187 m), 2nd(1187-1455 m), 3rd(1455-1670 m) & 4th(1670-3000 m). The total number of fixes for the 1st through 4th quartile was, 21,598, 21,633, 21,609 and 21,988 respectively.

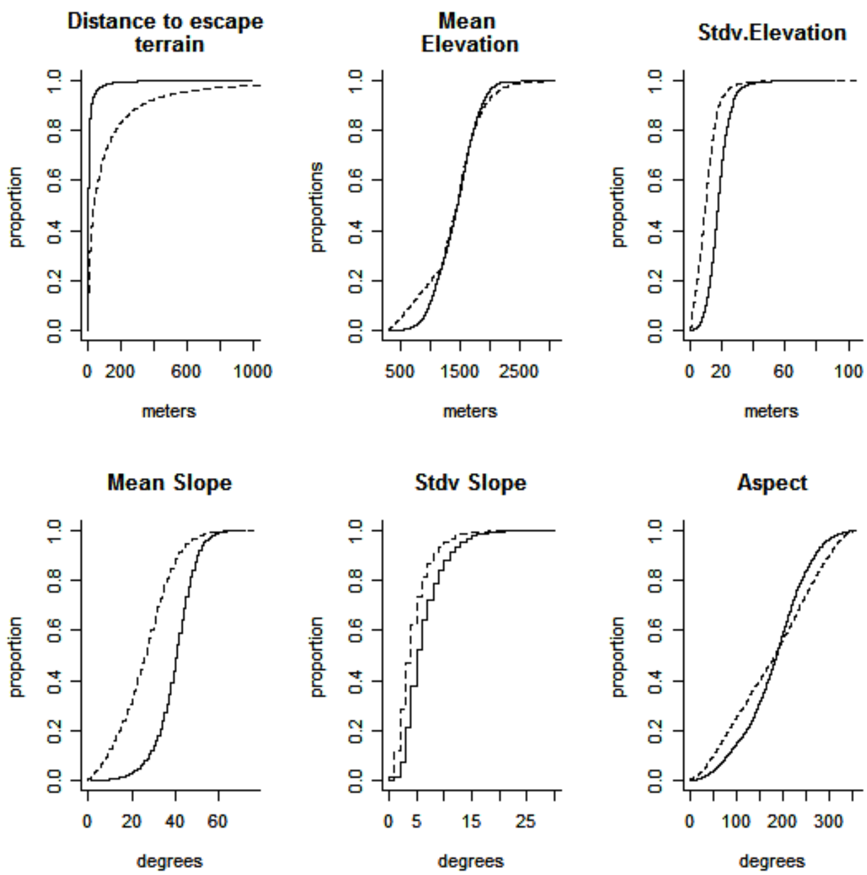

Fig. 10. Empirical cumulative frequency distributions of available (dotted) vs. goat locations (solid) for derived topographic predictor variables suggesting selection for areas closer to escape terrain and steeper slopes.

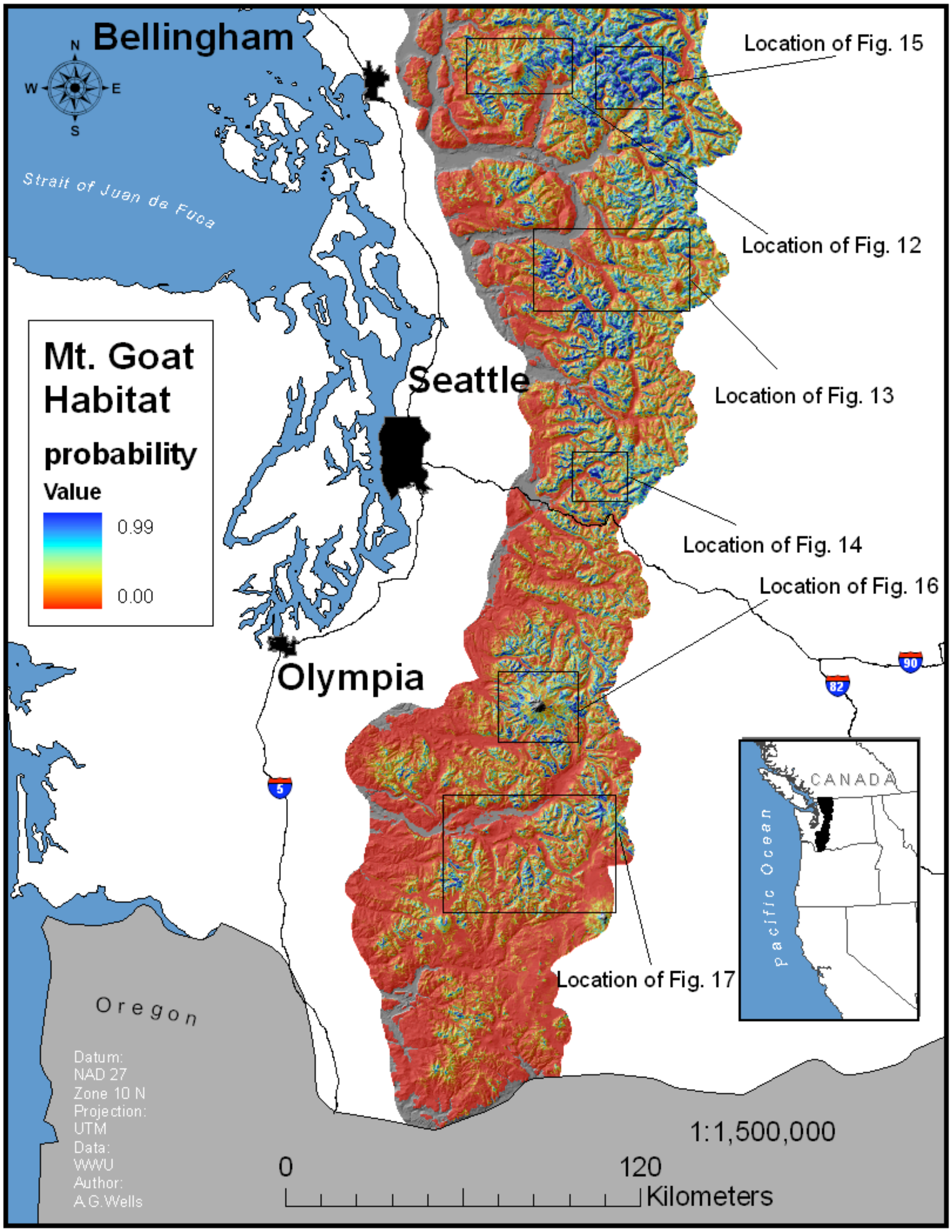

Fig. 11. Map showing continuous data layer of predicted potential mountain goat habitat for the western cascades of Washington based on elevation quartiles from the northern and southern halves of the Cascades, split along I-90, based on data from 39 GPS collared animals.

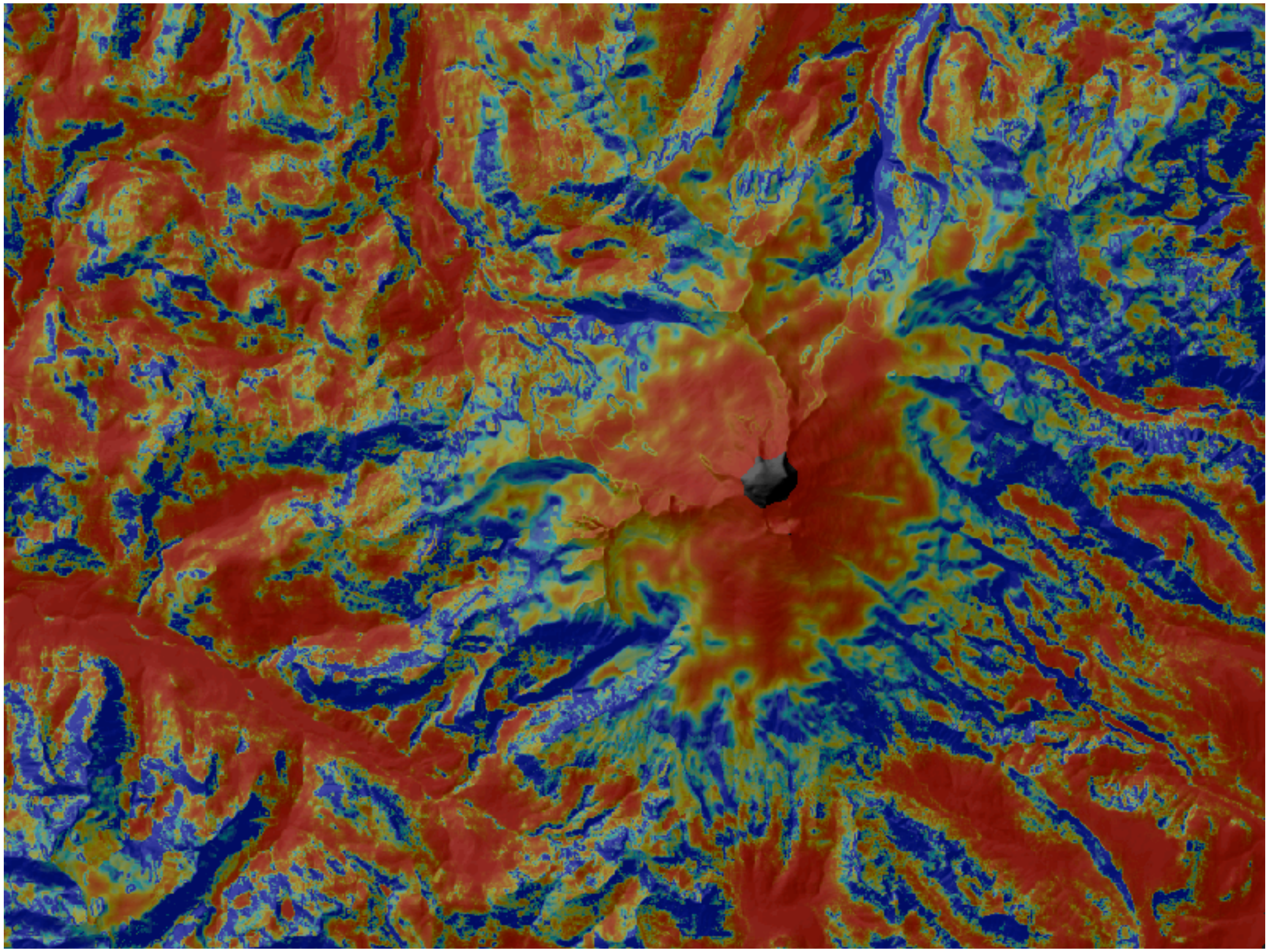

Fig. 12. Close up view of predicted potential mountain goat habitat in the vicinity of Mt. Baker, WA showing fairly contiguous habitat patches around the mountain. Blue designates high predicted probability while red denotes low

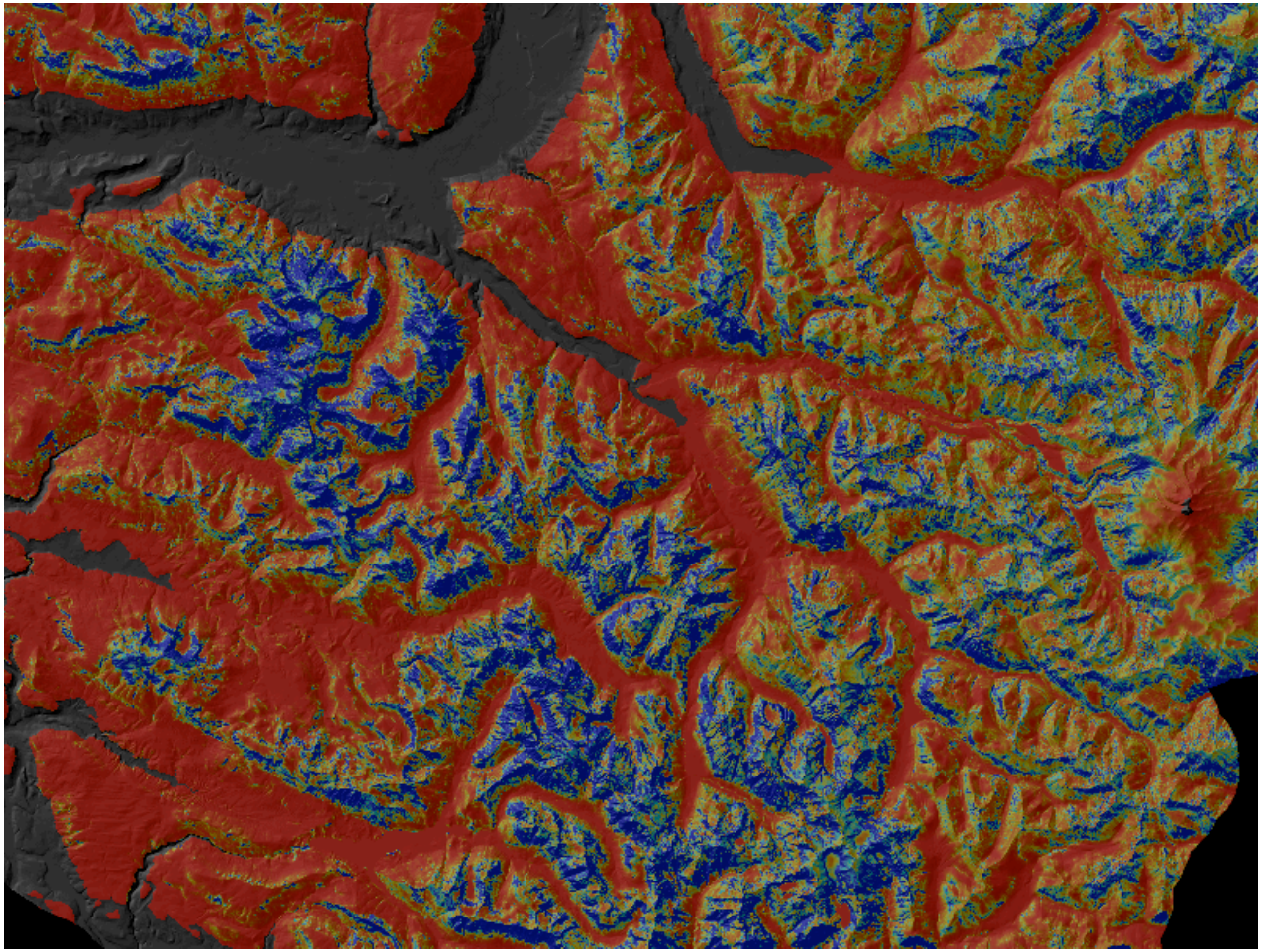

Fig. 13. Close up view of predicted potential mountain goat habitat around the Three Fingers-Whitehorse mountain complex (to the right) and of Glacier Peak, WA (to the left) showing a distinct isolation of the area from more easterly habitats. Blue designates high predicted probability while red denotes low.

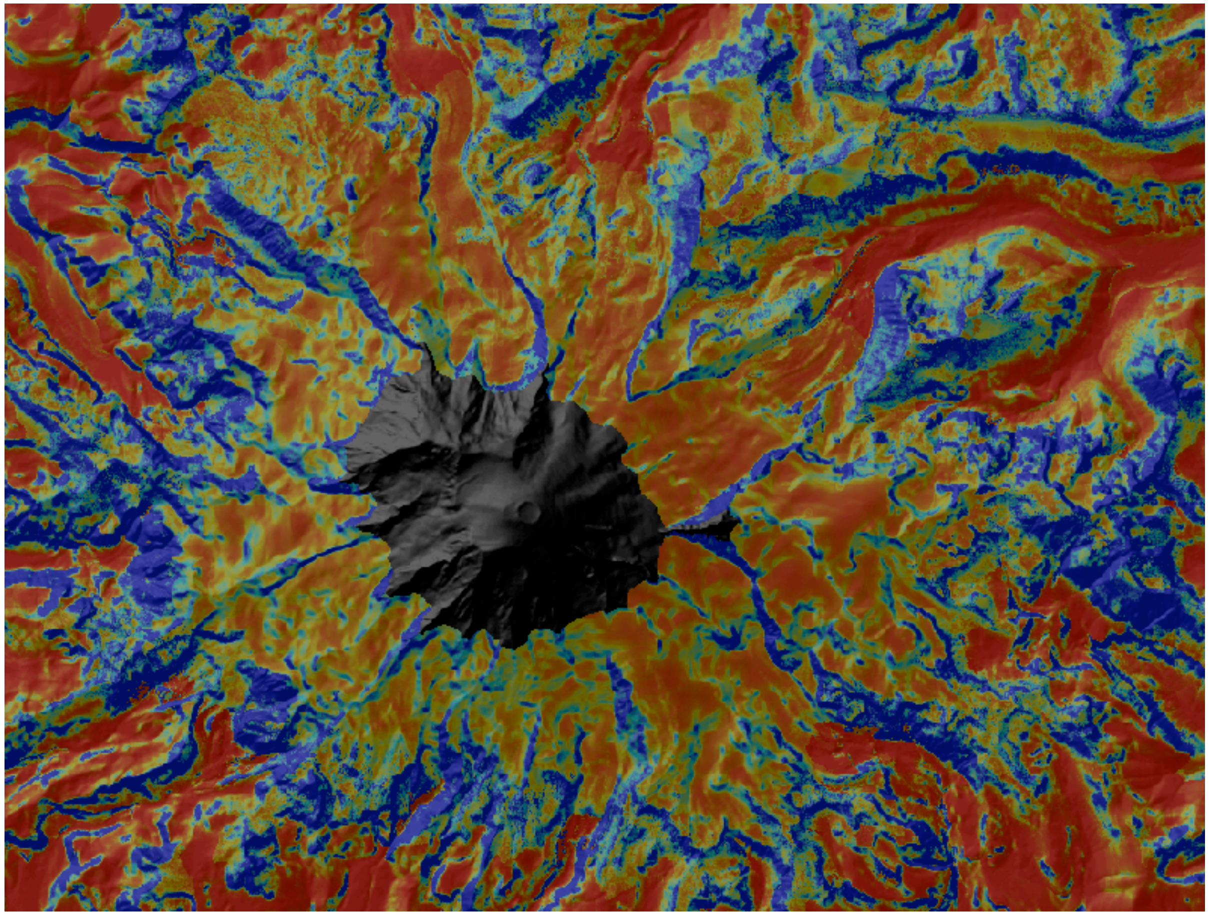

Fig. 14. Predicted potential mountain goat habitat around Mt. Rainier, WA showing a more striated pattern of habitat patches then those around Mt. Baker. Blue designates high predicted probability while red denotes low, with the grey summit falling above the highest observed mountain goat elevations and consequently outside of the analysis.

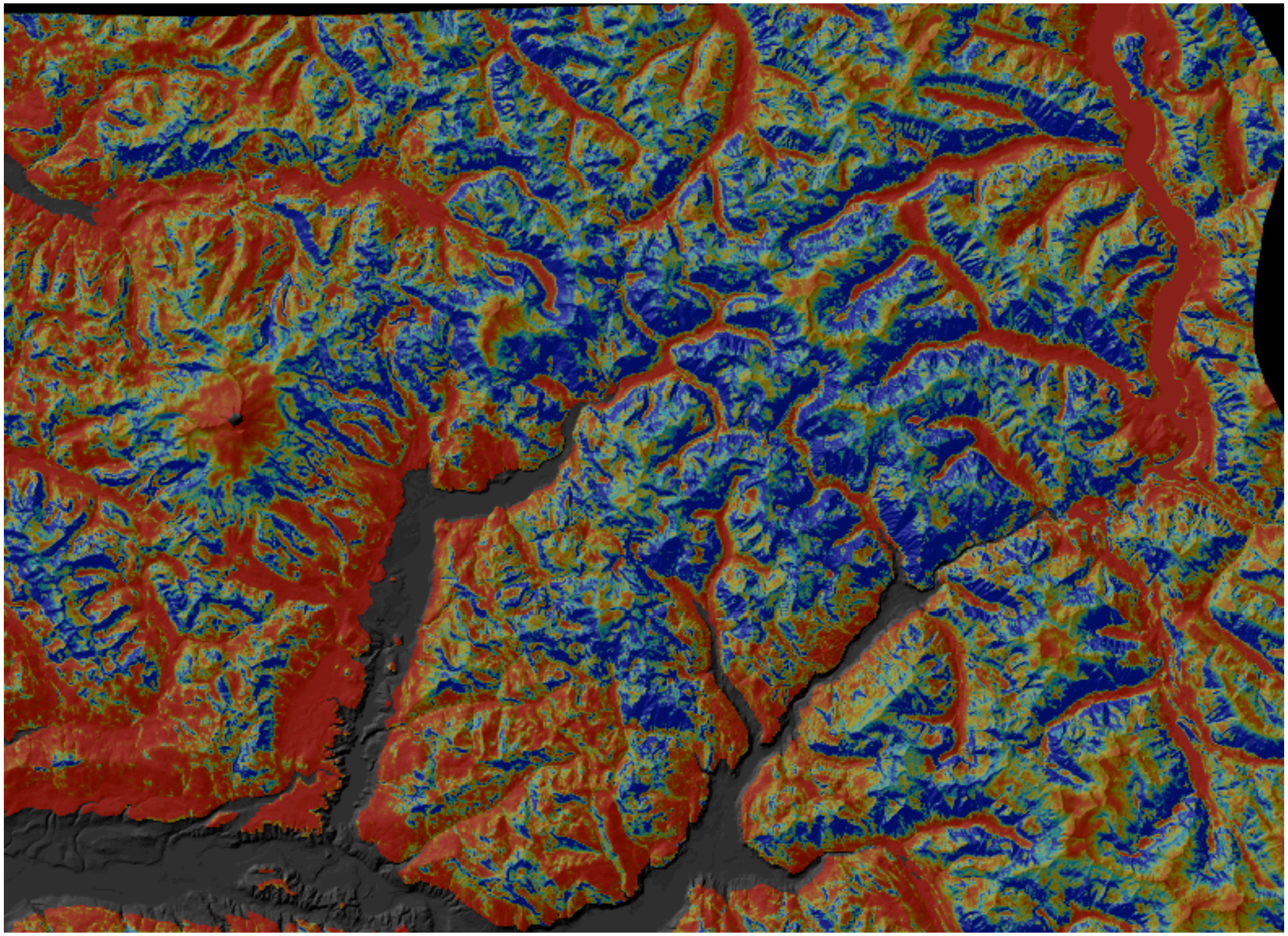

Fig. 15. Close up view of the area east of Mt. Baker, WA encompassing the North Cascade National Park and the Pickett Range showing some of the highest quality and most well connected predicted habitat despite having few observed mountain goats. The Canadian border forms the northern border of the image.

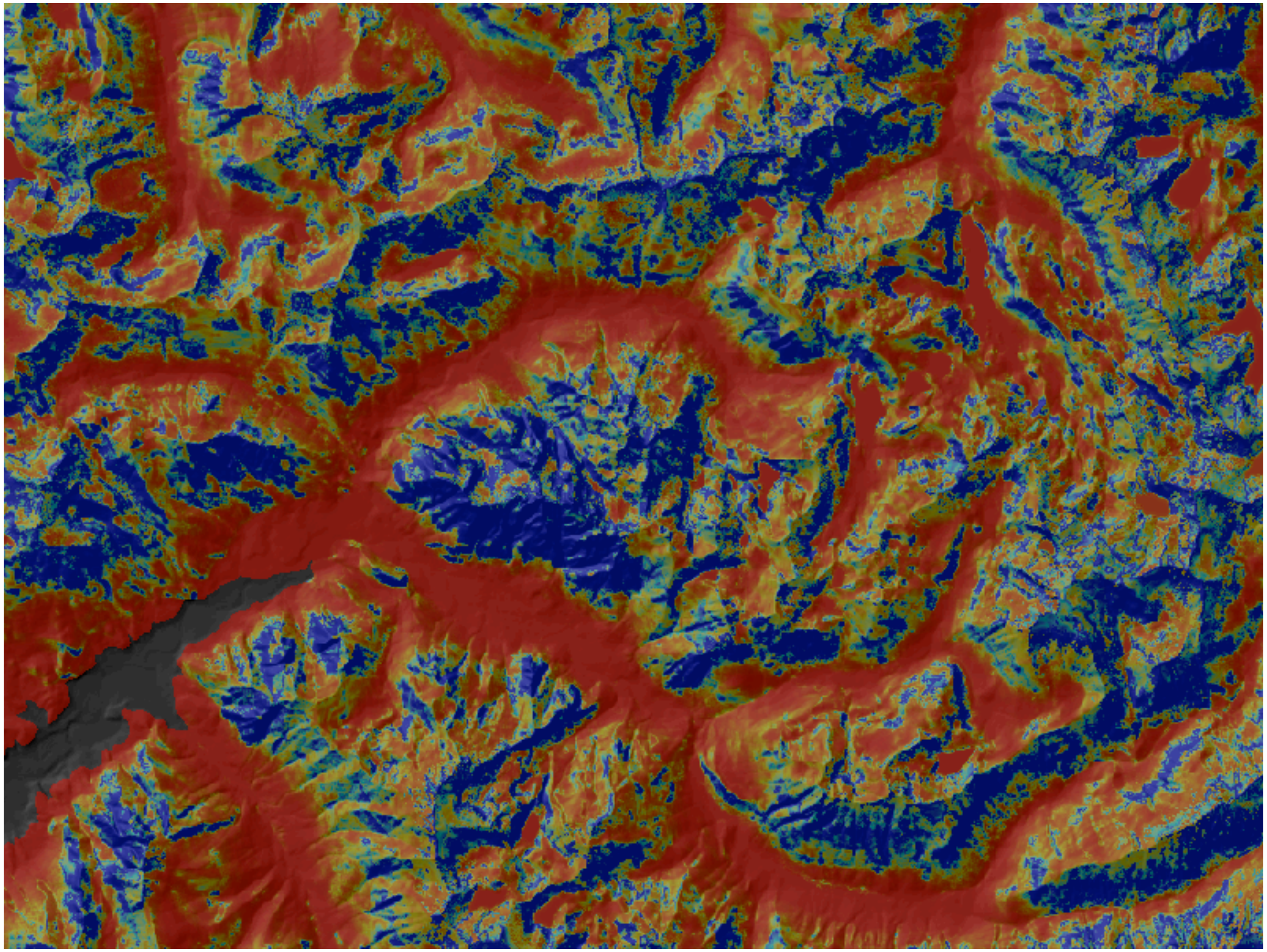

Fig. 16. Close up view of Garfield Mt. in the middle Cascades, a region with lots of predicted potential habitat but few mountain goats. Blue designates high predicted probability while red denotes low.

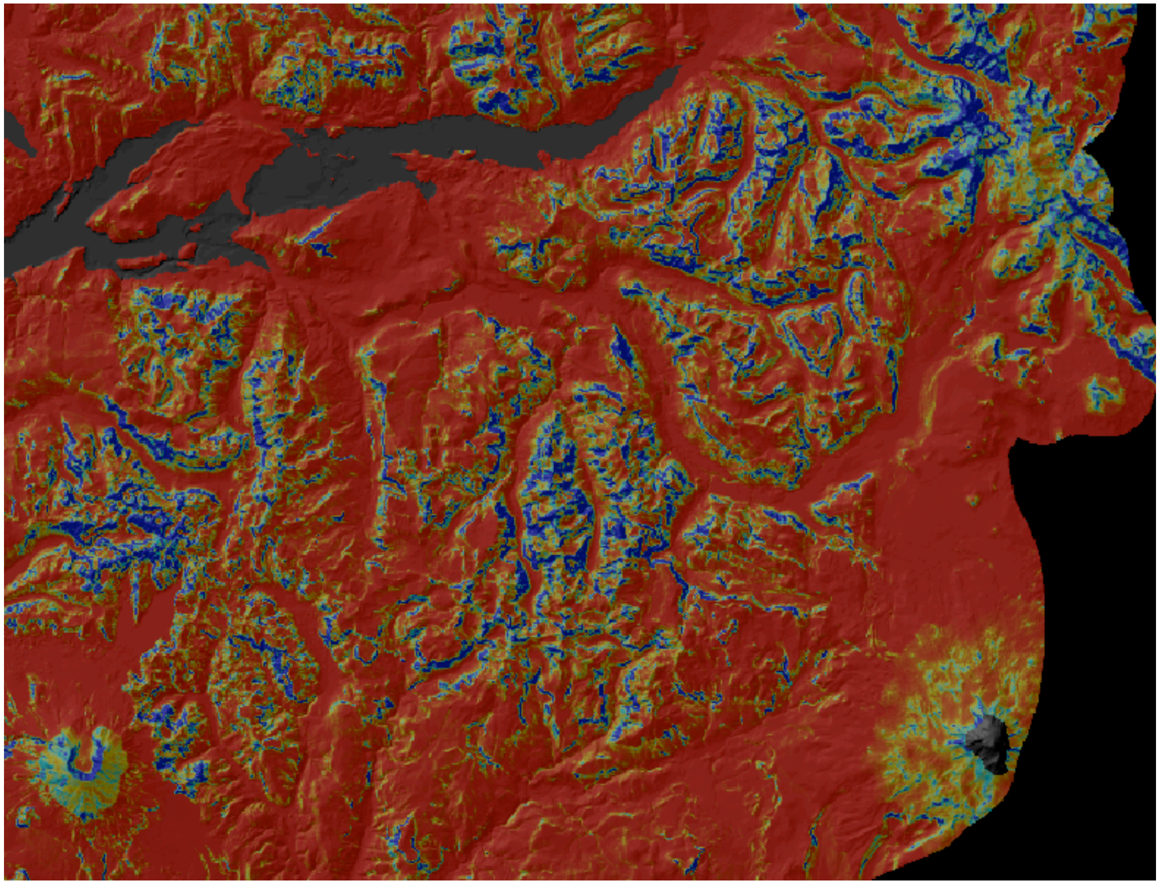

Fig. 17. Close up view of the southern Cascades depicting a more disjointed landscape of mountain goat habitat although supporting known populations of animals. Goat Rocks Wilderness area appears in the upper right, Mt. Adams (with marginal habitat at best) in the lower right and Mt. St. Helens in the lower left. Blue designates high predicted probability while red denotes low.

References

Adams, L.G. & Bailey, J.A. (1982) Population dynamics of mountain goats in the Sawatch Range, Colorado. *Journal of Wildlife Management* **46**, 1003-1009.

Ballard, W. (1977) Status and management of the mountain goat in Alaska. *Proceedings of the first international mountain goat symposium* (Samuel, W. & Macgregor, W.G. eds). Kalispell, Montana. **1,** 15-23.

Beyers, H.L. (2004) Hawth's analysis tools for ArcGIS. http://www.spatialecology.com/htools.

Brockway, D.G., Topik, C., Hemstrom, M.A. & Emmingham, W.H. (1983) *Plant association and management guide for the pacific silver fir zone.* USDA pub. **R6-ECOL-130a-1983**.

Burnham, K.P. & Anderson, D.R. (2002) *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*, 2nd edn. Springer-Verlag, New York.

Browning J., Kroll, KC, Grob, C., Ducey, C., Fassnacht, K., Alegria,J., Nighbert, J., Moeur, M., Fetterman, J., & Weyermann, D. (2003) *Interagency Vegetation Mapping Project (IVMP) Eastern Cascades Washington Province Version 1.0 for US Department of the Interior Bureau of Land Management/OSO and US Forest Service.* http://www.or.blm.gov/gis/projects/vegetation/

Cain, J.W., Krausman, P.R., Jansen B.D. & Morgart, J.R. (2005) Influence of topography and GPS fix interval on GPS collar performance. *Wildlife Society Bulletin*, **33**, 926-934.

Côté S.D. & Festa-Bianchet M. (2003) *Mountain Goat* in *Wild mammals of North America: Biology, management and conservation.* 2nd edn. (Feldhamer G.A., Thompson B.C. and Chapman, J.A. eds.) John Hopkins University Press, Baltimore, Maryland. 1061-1075.

Deckert, C. & Bolstad, P.V. (1996) Forest canopy, terrain, and distance effects on global positioning system point accuracy. *Photogrammetric Engineering & Remote Sensing*, **62**, 317-321.

D'eon, R.G., Serrouya, R., Smith, G. & Kochanny, C.O. (2002) GPS radiotelemetry error and bias in mountainous terrain. *Wildlife Society Bulletin*, **30**, 430-439.

Development Core Team. (2005) R: *A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austira. http://www.R-project.org

Di Orio, A.P., Callas, R. & Schaefer, R.J. (2003) Performance of two GPS telemetry collars under different habitat conditions. *Wildlife Society Bulletin*, **31**, 372-379.

Douglas, G.W. & Bliss, L.C. (1977) Alpine and high subalpine plant communities of the North Cascades Ranges, Washington and British Columbia. *Ecological Monographs.* **47**, 113-150.

Dussault C., Courtois, R., Ouellet, J.-P. & Huot, J. (1999) Evaluation of GPS telemetry collar performance for habitat studies in the boreal forest. *Wildlife Society Bulletin*, **27**, 965-972.

Ednenius, L. (1997) Field test of a GPS location system for moose *Alces alces* under Scandinavian boreal conditions. *Wildlife Biology*, **3**, 39-43.

Environmental Systems Research Institute. (2004) ArcInfo/ArcMap 9.0. Redlands, California, United States.

Fox, J.L., Smith, C.A., & Schoen, J.W. (1989) *Relation between mountain goats and their habitat in southeastern Alaska*. **PNW-GTR-246**

Fox, J.L. & Taber, R.D. (1981) *Site selection by mountain goats wintering in forest habitat*. **FS-PNW-Grant No. 153**.

Franklin, J.F. & Dryness, C.T. (1988) *Natural Vegetation of Oregon and Washington*. Oregon State University Press.

Frair, J.L., Nielson, S.E., Merrill, E.H., Lele, S.R., Boyce, M.S., Munor, R.H., Stenhouse, G.B. & Beyer, H.L. (2004) Removing GPS collar bias in habitat selection studies. *Journal of Applied Ecology*, **41**, 201-212.

Gamo, R.S. & Rumble, M.A. (2000) GPS radio collar 3D performance as influenced by forest structure and topography. *Biotelemety 15: Proceedings of the 15th International Symposium of Biotelemetry*. (eds Eiler, J.H., Alcorn, D.J. & Neuman,M.R) 464-473. International Society on Biotelemetry Wageningen, The Netherlands.

Gentleman R.C., Carey, V.J., Bates, D.M., Bolstad, B., Dettling, M., Dudoit, S., Ellis, B., Gautier, L., Ge, Y. Gentry, J., Hornik, K., Hothorn, T., Huber, W., Iacus, S., Irizarry, R., Li, F.L.C., Maechler, M. Rossini, A.J., Sawitzki, G., Smith, C., Smyth, G., Tierney, L., Yang, J.Y.H. & Zhnag, J. (2004) Bioconductor: Open software development for computational biology and bioinformatics. *Genome Biology,* **5**, R80, http://genomebiology.com/2004/5/R80.

Gerlach, F.L., & Jasumback A.E. (1989) *Global positioning system canopy effects study*. USDA Forest Service, Technology and Development Center, Missoula, MT.

Gross, J.E., Kneeland, M.C., Reed, D.F. & Reich, R.M. (2002) GIS-based habitat models for mountain goats. *Journal of Mammalogy,* **83**,218-228.

Harrell, F.E. (2001) *Regression Modeling Strategies, with Applications to Linear Models, Survival Analysis and Logistic Regression*. Springer, New York.

Hayden, J.A. (1984) Introduced mountain goats in the snake river range, Idaho: Characteristics of vigourous population growth. *Northern wild sheep and goat council: Proceedings of the biennial symposium*. (Hoefs, M.ed.) Whithorse, Yukon Canada. **4**, 94-119.

Heagerty, P.J. (1999) Marginally specified logistic-normal models for longitudinal binary data. *Biometrics*. **55**, 688-698.

Hoffman-Wellenhof, B.H., Lichtenegger, H. & Collins, J. (1997) *GPS: theory and practice*, 4th edn. SpringerWien, New York.

Horton, N.J., & Lipsitz, S.R. (1999) Review of software to fit generalized estimating equation regression models. *The American Statistician*. **53**, 160-169.

Hosmer D.W. & Lemeshow, S. (2000) *Applied Logistic Regression*, 2nd ed. John Wiley & Sons, New York, NY.

Johnson, C.E. & Barton, C.C. (2004) Where in the world are my field plots? Using GPS effectively in environmental studies. *Frontiers in Ecology and the Environment*, **2**, 475-482.

Johnson, R.E. & Cassidy, K.M. (1997) *Washington Gap Project Mammal Distribution Models, version 5.* Seattle, WA. Washington Cooperative Fish and Wildlife Research Unit. ftp://ftp.dfw.wa.gov/pub/gapdata/mammals.

Johnson, R.L. (1983) *Mountain Goats and Mountain Sheep of Washington.* Washington state game department biological bulletin no. **18**.

Keating, K.A & Cherry, S. 2004. Use and interpretation of logistic regression in habitat-selection studies. *Journal of Wildlife Management,* **68**, 774-789.

Kuch, L. (1977) The impacts of hunting on Idaho's Pahsimeroi mountain goat herd. *Proceedings of the first international mountain goat symposium* (Samuel, W. & Macgregor, W.G. eds). Kalispell, Montana. **1,** 114-125.

Lefsky, M.A., W.B. Cohen, G.G. Parker & D.J. Harding. (2002) Lidar remote sensing for ecosystem studies. *Bioscience*, **52**,19-30.

Licoppe, A.M. & Lievens, J. (2001) The first tracing results from a female free-ranging red deer (*Cervus elaphus*) fitted with a GPS collar in Ardenne, Belgium. *Tracking animals with GPS: An international conference held at the Macaulay Land Use Research Institute Aberdeen 12-13 March 2001.* Macaulay Land Use Research Institute, Aberdeen, Scotland UK. 25-28.

Macgregor, W.C. (1977) Status of mountain goats in British Columbia. *Proceedings of the first international mountain goat symposium*. (Samuel, W. & Macgregor, W.G. eds.) Kalispell, Montana. **1**, 24-28.

Manly, B.F.J., McDonald, L.L., Thomas, D.L., McDonald, T.L., & Wallace, E.P. (2002) *Resource selection by animals. Statistical design and anlaysis for field studies.* 2nd ed. Kulwer Academic Publishers. Dordrecht, The Netherlands.

Menard, S. (2000) Coefficients of determination for multiple logistic regression analysis. *American Statistical Association*, **54**, 17-24.

Moen, R., Pastor, J. & Cohen, Y. (1997) Accuracy of GPS telemetry collar locations with differential correction. *Journal of Wildlife Management*, **61**, 530-539.

Nagorsen, D.W. & Keddie, G. (2000) Late pleistocene mountain goats (*Oreamnos americanus*) from Vancounver Island: biogeographic implications. *Journal of Mammalogy*, **81**, 666-675.

O'Neil J., Kroll, KC, Grob, C., Ducey, C., Fassnacht, K., Alegria,J., Nighbert, J., Moeur, M., Fetterman, J., & Weyermann, D. (2002) *Interagency Vegetation Mapping Project (IVMP) Western Cascades Washington Province Version 2.0 for US Department of the Interior Bureau of Land Management/OSO and US Forest Service.* http://www.or.blm.gov/gis/projects/vegetation/

Pendergast, J.F., Gange, S.J., Newton, M.A., Lindstrom, M.J., Palta, M., & Fisher, M.R. (1996) A survey of methods for analyzing clustered binary response data. *International Statistical Review*, **64**, 89-118.

Pearce, J. & Ferrier, S. (2000) Evaluating the predictive performance of habitat models developed using logistic regression. *Ecological Modelling*, **133**, 225-245.

Rempel, R.S., Rodgers, A.T. & Abraham K.F. (1995) Performance of a GPS animal location system under boreal forest canopy. *Journal of Wildlife Management*, **59**, 543-551.

Rempel, R.S. & Rodgers, A.R. (1997) Effects of differential correction on accuracy of a GPS animal location system. *Journal of Wildlife Management*, **61**, 1997.

Rodgers, A.B., (2001) Tracking animals with GPS: the first ten years. *Tracking animals with GPS: An international conference held at the Macaulay Land Use Research Institute Aberdeen 12-13 March 2001*. pp 1-10. Macaulay Land Use Research Institute, Aberdeen, Scotland UK.

Sager, K.A. (2005) *Black bear distribution patterns in a temperate forest environment, Olympic National Park.* Master thesis, University of Idaho.

Taylor, R.J. (1986) Plant life of the North Cascades: Lake-Chelan-Sawtooth Ridge Stehekin Valley and Glacier Peak. *Dougals Occasional Papers*. Washington Native Plant Society, **2**.

Taylor, S.D. (2002) *Addressing observation bias in a GPS-telemetry study of coastal mountain goats.* Masters thesis, University of British Columbia.

Teachman, J. & Crowder, K. (2002) Multilevel models in family research: some conceptual and methodological issues. *Journal of Marriage and Family*, **64**, 280-294.

Topik, C., Halverson, N.M. and Brockway, D.G. (1986) *Plant Association and Management Guide for the Western hemlock Zone.* USDA pub. **PNR R6-ECOL-230A-1986**.

USDA (2006) http://www.skimountaineer.com/CascadeSki/CascadeSnowNWAC.php

Varley, N.C. (1994) Summer-fall habitat use and fall diets of mountain goats and bighorn sheep in the Absaroka, Montana*.* *Biennial Symposium of the Northern Wild Sheep and Goat Council* (Pybus, M. & Wishart, B. eds.) Cranbook, British Columbia Canada. **9**:131-138.

Welch, S. & Raedeke, K.J. (1990) *Status of the mountain goat population on White Chuck Mountain, North Cascades, Washington: Final report to the Washington State Department of Wildlife and USDA Forest Service, Mount Baker-Snoqualmie National Forest*. College of Forest Resources; University of Washington, Seattle, WA.

Zar, J.H. (1996) *Biostatistical Analysis*, 3rd edn. Prentice Hall, New Jersey.

Appendix

A. Sky Visibility

The sky visibility algorithm performed a discrete approximation of a hemispherical integral and worked with a large DEM. The algorithm generated a series of hillshade grids, each with the sun at a different elevation and azimuth angle. For a given sun elevation and azimuth, the hillshade function determined whether each grid cell fell in full sun or shadow. A final output grid consisted of a weighted tally of the number of "sun hits" each grid cell received. This weighted tally expressed the percentage of the maximum possible number of "sun hits" (the number of azimuth angles times the number of elevation angles). Each of the initial grids received weighting using the cosine of the elevation angle. This weighting corrected for the fact that low elevation angles represented a greater section of sky than high elevation angles. The net result quantified the percentage of the sky visible from each grid cell, based on surrounding topography. Unobstructed sky provided access to more satellites; topographic obstructions in one or more portions of the sky blocked access

B. Non-linear mixed macro

This is the macro written for implementation in SAS that executed the non-linear mixed modeling scheme for the GPS PAR model. The model executes an ordinary logistic regression to generate initial parameter estimates prior to using the non-linear modeling. This macro was used during model selection to account for the random effects error structure due to the repeated measure of GPS PAR at each sample site.

```
%macro Logisticmixed(data1,data2,depvar,nvars,nparm,variables,parms);
title "Initial logistic fit with covariates:&variables";
proc logistic data=&data1 descending outest=betas;
   model &depvar= &variables /aggregate=(cluster) scale=none rsquare lackfit;
         ods output FitStatistics=Fitstat LackFitChiSq=HLtest RSquare=r2;
*GoodnessOfFit=gof;
data betas; set betas;
array x{&nparm} intercept &variables;
array b{&nparm} &parms;
 do i=1 to &nparm;
   b{i}=x{i};
  end;
 keep &parms;

proc nlmixed data=&data1 technique=nrridg maxiter=500 maxfunc=500;
parms s=1 / data=&data2;
 array b{&nparm} &parms;
 array x{&nvars} &variables;
 eta=ranvar+b{1};
 do i=1 to &nvars ;
  eta=eta+b{i+1}*x{i};
  end;
  model &depvar ~ binary(1-1/exp(eta));
  random  ranvar ~ normal(0,s*s) subject=cluster;
```

```
  ods output FitStatistics=FitStatistics;

data mixedresult;
   set FitStatistics;
   length variables $ 50;
   keep AICc variables;
   if Descr= "AICC (smaller is better)" then do;
      AICc=Value;
            variables= "&variables";
            output;
          end;
   title "subset:&variables";
   data summary; set summary mixedresult Fitstat HLtest r2 ;
   run;

%mend logisticmixed:
```